ESSAYS ON URBAN ECONOMICS
SPECIAL FOCUS ON NEW ZEALAND HOUSING MARKETS

BY

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DISSERTATION

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ABSTRACT

This dissertation consists of three chapters on the New Zealand housing market. The first chapter, titled “Salience of Hazard Disclosure and House Prices: Evidence from Christchurch, New Zealand,” addresses the impacts of providing precise salient earthquake hazard information on property values. Taking advantage of the land liquefaction zoning, known as the Technical Category (TC) zoning, following the 2010-2011 earthquake sequence (EQS) in Christchurch, I estimate the impacts of precise salient earthquake hazard information on property values. Using the property transaction data from 2000 to 2008 in the City of Christchurch, I first verify that the inherent liquefaction hazard was not capitalized before the 2010-2011 EQS. Next, exploring the property transaction data that spans 7 years before and after the TC zoning from 2005 to 2018, I find that the EQS prepared the market for a price change to liquefaction hazard. The area-wide TC zoning clarified the relative liquefaction hazard risks and reinforced the price change. Over the 7 years after zoning, average property values declined significantly by 20% in TC3 (high liquefaction risk areas), and 7% in TC2 (medium liquefaction risk areas). Pricing of housing is also found to incorporate the TC information quickly. Moreover, property values increased with distance to residential red zones (areas where liquefaction damage was beyond economical repair) the most in TC3 after the EQS.

The second chapter, titled “Is There a Slope Discount?” is joint work with Geoffrey Hewings. This chapter attends to the construction of more reliable quality-adjusted land price indices and focuses on the physical attributes of land that intrinsically confine land use and possibly affect land values, land slope. In particular, we investigate if there is a

slope discount to land price and address the role of land slope in forming more reliable constant quality land price indices and aggregate house price indices. We find while land slope discounts the unit land price, it has a small effect on quality-adjusted land price indices in selected neighborhoods in Auckland, New Zealand, where sloped terrain is common.

The third chapter titled “Does Proximity to School Still Matter Once Access to Your Preferred School Zone Has Already Been Secured?” is joint work with Sandy Dall’erba. This chapter develops the existing literature on proximity to school further by assessing the role of proximity to school on housing prices once access to the preferred school has been secured. We relax the assumption of uniform marginal effects of proximity to school and exploit the power of the quantile regression approach to test whether proximity is valued the same at the higher and lower end of the housing market. Using property transaction data from four school enrollment zones in Auckland, New Zealand, we find that in the most sought-after school zones, 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.

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Contents

Chapter 1

Salience of Hazard Disclosure and House Prices: Evidence from Christchurch, New Zealand

1.1 Introduction

Continued research on natural disaster and its impacts on economics and human environments is critical as natural hazards occur not only more frequently but also at unprecedented scales and cause enormous loss globally in recent decades. According to Lloyds City Risk Index, measured by percent of annual GDP at risk, natural catastrophe and climate change are the most significant threats to the world economy, placing 0.47% of the world GDP at risk per annum. Among the natural catastrophe and climate category, floods and earthquakes are the two major threats that led to 0.12% and 0.10% global GDP at risk per year.

New Zealand is ranked the second in the world for expected losses, as a percentage of GDP, that could occur from a natural hazard in any given year (Lloyds Global Underinsurance report 2018).[1] The estimated annual losses amount to 0.66% of New Zealand's GDP. Researchers in New Zealand and around the world have long recommended disclosure of the hazardousness of locations through maps and land use policies to increase public awareness of the potential for natural hazards when households decide on residential locations (Montz, 1993).

The empirical studies regarding impacts of hazard disclosure (earthquakes and volcanic

[1] This report is available at Lloyd's Risk Report.

eruptions) on property values from different parts of the world have appeared to generate a consensus that there are adverse short-term effects but no long-term effects of hazard disclosure and occurrence of the event itself on property values (Palm, 1981; Montz, 1987, 1993; MacDonald *et al.*, 1987; Montz and Tobin, 1988; Tobin and Montz, 1988, 1994; Bernknopf *et al.*, 1990; Lambley and Cordery, 1991; Beron *et al.*, 1997; Naoi *et al.*, 2009). However, concerning flood hazards, the empirical results are inconclusive in that the impacts on property values depend on whether the location of the floodplain is inland or coastal.[2] As pointed out by Palm (1981), hazard disclosure through zone maps was found to be not very effective, for hazard zone maps are often not at a scale at which the location of individual properties could be located. Even more critically, sometimes, the zones themselves do not encompass areas most susceptible to hazard-associated damages.

Sitting on the boundary of the world's two colossal tectonic plates, New Zealand is highly prone to earthquakes. While earthquakes can help to create the spectacular landscape through mountain building and erosion, they also generate hazards to the built environment mainly through ground shaking, fault rupture, subsidence, landslides, and ground deformation of soil due to liquefaction.[3]

As an important seismic hazard, liquefaction has produced significant damage to the natural and built environments in past earthquakes (e.g., the historical earthquakes of Northridge in 1994, Kobe in 1995, Loma Prieta, San Francisco, in 1989 and the recent earthquakes of Chili in 2010, Christchurch, New Zealand, in 2010 – 2011, Japan in 2011),

[2] Literature on flood risk discourse includes but not limited to Troy and Romm (2004); Daniel *et al.* (2009); Bin and Landry (2013). Please see Beltrán *et al.* (2018) for a meta-analysis.

[3] See GNS Science: Earthquake Hazards or Pacific Northwest Seismic Network: Earthquake Hazards Overview.

and it has proved to be one of the most costly phenomena. Although liquefaction has been recognized as a significant engineering issue and widely studied by environmental and engineering society since the 1960s, few studies have looked at how aware the society is and how responsive the market is to liquefaction hazard. According to seismic data, seismic liquefaction and its damage to foundations and upper structures since the beginning of this century were more frequent than before in many places around the world (Huang and Xiong, 2017). Therefore, understanding how the property market responds to this hazard is important because knowledge about people's reactions (and resulting decisions) to a hazard has implications for the design of urban resilience to disasters and limit losses.

The fundamental hypothesis of hazard literature is that the impact of natural hazards and succeeding policy intervention on the human environment (such as development and land use) will be reflected in values and spatial locations of residential properties (Montz and Tobin, 1988). In this paper, I utilize the 2010-2011 sequence of earthquakes in Canterbury and the subsequent residential land zoning in terms of future liquefaction performance, outlined by the three-level Technical Categories (TCs), to analyze whether the negative impacts of the earthquake and the liquefaction hazard zoning are manifested in the property values. Moreover, the analysis will be extended to explore how long the adverse effects last and how long it takes the property values to recover to the pre-earthquake price levels. First, using monthly transaction data from 2000 to 2008 for the City of Christchurch and the 2002 and 2005 liquefaction hazard maps from the multi-stage liquefaction study in Christchurch, I verify that the long-recognized liquefaction hazard was not capitalized before the 2010-2011 earthquake sequence. Then, using monthly transaction data from 2005 to 2018 in the

City of Christchurch, I adopt a standard hedonic model with both difference-in-difference (DID) and event study designs and find that the market had gained some knowledge on the severity of liquefaction hazard through the earthquake sequence. After the liquefaction-hazard-based TCs were announced, average property values declined significantly by about 22% in TC3, the most liquefaction-prone TC, while property values declined by 7% in TC2, the second most liquefaction-prone TC. The price difference between TC3 and TC2 is still as significant as about 10% seven years (in 2018) after TC announcement. These findings are validated using both the spatial conditionally parametric–semiparametric and the boundary discontinuity models and are robust to alternative specifications for earthquake impact period and falsification tests. Moreover, I find that the liquefaction hazard also led to price discounts to proximity to the residential red zones (severely liquefied residential areas); this proximity penalty is the largest in TC3.

The primary contributions of this paper, in comparison to previous studies, are as follows. First, while previous studies on disclosure of earthquake hazard through zone maps focus on the impacts of existing zone maps, this paper illustrates the impacts of an earthquake-induced hazard map disclosed immediately after significant earthquakes. Second, previous studies mainly use DID techniques to evaluate the impacts of change in risk perceptions after earthquakes on property prices. This paper provides a research design that enables studying the earthquake-induced hazard zoning directly instead of changes in risk perception or classification, as well as acknowledges the possible change in price structure induced by hazard-triggering earthquakes. Moreover, this paper provides evidence on the salience of hazard information, given the sharpen attention to liquefaction hazard after the 2010-2011

Canterbury earthquake sequence.

The remainder of the paper is organized as follows. Section 1.2 describes the 2010-2011 Canterbury Earthquake sequence. Section 1.3 reviews the related literature. Section 1.4 proposes the hypotheses and theoretical framework. Section 1.5 presents the data set. Section 1.6 presents and discusses main results as well as robustness analysis. Section 1.7 concludes.

1.2 2010-2011 Canterbury Earthquake Sequence

Earthquakes are not uncommon in Christchurch and surrounding Canterbury region but were never as frequent or of magnitude as those experienced before the series of 2010-2011 in Canterbury and Christchurch. Four major shocks and more than 10,000 aftershocks were recorded in Christchurch and the surrounding areas between September 2010 and December 2011. The sequence of events was as follows:

- At 4:35 am (New Zealand Standard Time, NZST) on 4 September 2010, Canterbury New Zealand was struck by a moment magnitude M_W 7.1 earthquake at a shallow depth of 10 km (6.2 miles). The epicenter was located about 9 km (5.6 miles) south-east of the town of Darfield, which is 40 km (25 miles) west of Christchurch, New Zealand's second-largest city. This earthquake did not cause any fatality. However, it generated devastating damage to houses, triggered widespread liquefaction, and caused disruption to water power and sewerage infrastructure.
- At 12:51 pm (NZST) on 22 February 2011, the city of Christchurch was devastated by an M_W 6.3 earthquake (aftershock) that was centered only 10 km (6 miles) south-east of central Christchurch at a depth of 5 km (3 miles). It caused extensive and recurrent

liquefaction, severely damaged the land, shattered buildings, and killed 185 people.

- At 2:20 pm (NZST) on Monday 13 June 2011, a significant M_W 6.4 aftershock was felt in Christchurch, with an epicenter 10 km (6 miles) south-east of Christchurch at a depth of 6 km (3.7 miles), following an M_W 5.6 aftershock east of Christchurch at a depth of 9 km (5.6 miles) at 1 pm. They both caused further liquefaction and damage to buildings and land.
- At 1:58 pm (NZST) on 23 December 2011, an M_W 5.8 aftershock struck offshore from Christchurch at a depth of 7 km (4 miles), followed by an M_W 5.3 aftershock at 2:06 pm and an M_W 6.0 aftershock at 3:18 pm.

The land damage due to the soil liquefaction in some residential areas in the greater Christchurch area as a result of the long-lasting 2010-2011 earthquake sequence was severe. To lead and coordinate the recovery and rebuild from these disastrous earthquake events, the Canterbury Earthquake Recovery Authority (CERA) was established in March 2011. On 23 June 2011, every residential property in Christchurch was zoned into four colored categories: red, orange, green, and white, as shown in Figure 1.1. In the residential red zone, the land was severely damaged beyond economical repair. Initially, 5,100 properties were identified in the residential red zone. Land needing further evaluation was categorized as orange. At first, 10,500 properties were in the orange zone and waiting for assessment. In the green zone, the land was suitable for the repairing and rebuilding of residential properties. Port Hills and the central city of Christchurch were categorized as the white zone. A case study by EQ Recovering Learning in 2016 reported that by October 2012, all properties in residential areas of greater Christchurch, apart from the central city, had been zoned either red or green. About 180,000 properties out of 190,000 properties assessed in greater Christchurch were zoned green. These property owners could proceed with insurance claims relating to land damage and the repair or rebuilding of their properties.[4]

Based on the expected liquefaction performance in future significant earthquakes, the residential green zone was further divided into three Technical Categories (TCs) that served as guides to site investigation and the appropriate foundation required for each property. The ”Residential Foundation Technical Categories” map, shown in Figure 1.2, was first published by the Ministry of Business, Innovation and Employment (MBIE) on 28 October 2011. The public was informed on the same day the website on which land's technical category could be easily found by searching property address.

TCs were established using the information, including observed land and property damage resulted from the 2010-2011 earthquake sequence, groundwater information, and soil conditions best known at the time. The land is classified as TC1 (gray) if future land damage from liquefaction is unlikely so that it is appropriate to use standard residential foundation assessment and construction. TC2 (yellow) indicates that minor to moderate liquefaction damage to the land is possible in future large earthquakes so that it may require shallow ground investigations for repairing or replacing foundations. TC3 (blue) signifies that moderate to severe liquefaction damage to the land is possible in future large earthquakes so that it may require geotechnical engineering assessment to select the proper foundation for repairing or rebuilding.[5]

As a consequence of the 2010-2011 earthquake sequence, approximately 60,000 residential

[4] See Land Zoning Policy and the Residential Red Zone: Responding to land damage and risk to life (2016).

[5] Information is accessed at Christchurch City Council: Technical categories information.

buildings in Christchurch were affected by liquefaction, among which about 20,000 were severely affected by liquefaction, and around 8,000 out the 20,000 were in the residential red zone where damage was beyond economical repair (Cubrinovski, 2013). Housing supply statistics from Christchurch City Council show that 20,100 new residential buildings were built between 2011 and 2018, among which 13,600 were net new residential buildings and 6,500 were replacement houses; the majority of new house construction (an annual average of 64%) took place in greenfield areas[6] of the city.

As of 2016, the estimated construction cost of rebuild by the Reserve Bank of New Zealand (RBNZ) amounted to NZ$40 billion (in 2015 New Zealand dollars), and the rate of rebuild was estimated to cost approximately the equivalent of 1.5% of potential GDP per year with the rebuild expected to extend beyond 2020.[7] In addition, the exceptionally high level of earthquake insurance coverage (more than 90% of residential homes in New Zealand have earthquake insurance) made the Canterbury earthquake sequence one of the most heavily insured earthquake events in history.

The 2010-2011 Canterbury earthquake sequence and the resulted area-wide liquefaction hazard zoning provide a unique opportunity to evaluate hazard disclosure and salience of hazard information, targeting an area-wide specific earthquake hazard as opposed to an area-wide overall seismic risk or a specific hazard disclosure in a narrower area. First, the 2010-2011 Canterbury earthquake sequence brought sharp attention to liquefaction hazard and significantly increased public understanding of liquefaction. In addition, the liquefaction

6 Definition of Greenfield area by Christchurch City Council: area of previously undeveloped land used for agriculture, landscape design, or left vacant, which has been identified as being suitable for development; generally located on the outskirts of an urban area.

7 See RBNZ: Bulletin Vol.79, No.3 (Feb 2016).

hazard assessment was performed on an area-wide basis covering all flat residential land. Moreover, the result of the liquefaction hazard assessment (three-level TC land zoning) was disclosed at the most sensitive time, only a few months after the long-lasting earthquake sequence and easily accessible at the property level. As a result, the information on land hazard zoning disclosed is well-understood by the general public. However, the closely time-spaced earthquakes and the resulted liquefaction hazard zoning pose a challenge for the identification of the causal effect of liquefaction hazard zoning for that the establishment of TC is endogenous to observed liquefaction damage triggered by the earthquake sequence. The market may respond to the observed cumulative liquefaction damage even in the absence of the subsequent hazard classification. I overcome the identification challenge by controlling for the long-run heterogeneous earthquake effects.

1.3 Literature Review

This paper contributes to the literature on the capitalization of seismic risk through the hazard zone map disclosure. Brookshire *et al.* (1985) examine the effects of disclosure of a risk hazard map (in a Special Studies Zone, SSZ, or not) in California on single-family housing prices. They find that disclosure of the earthquake hazard zones has a significantly negative impact on prices (in 1978). More recently, Singh (2019) studies the impacts of disclosure of earthquake fault maps in California, revision of the maps over time in particular, on property values in the City of Los Angeles. She uses the DID framework and finds that house prices increase by 1.8% per mile increase in distance from the fault zone. She also finds suggestive evidence that compared to Whites Blacks and Hispanics are less willing to trade consumption for lower earthquake risk. This paper contributes to this strand of literature by studying the long-run and dynamic impacts of an earthquake-induced area-wide hazard zoning by implementing a quasi-experimental research design to identify the causal effect of hazard zoning. The area-wide hazard zoning covering all flat residential land in Christchurch allows studying market response to hazard disclosure at a broader scale instead of the response concentrated inside/outside or around the boundaries of the hazard zones (e.g., fault zone).

This paper also speaks to the literature by studying a specific earthquake risk on property values. There have been relatively few studies on the impacts of different types of earthquake risks on housing and land prices despite the obvious relevance to effective disaster prevention policies. Nakagawa *et al.* (2007, 2009) address the effect of earthquake risk on land price and housing rents using the index of earthquake risk in terms of potential damage to buildings due to initial earthquake shocks compiled for the entire metropolitan area by the Tokyo Metropolitan Government (Bureau of Urban Development, 1998), respectively. They show that land prices and housing rents were lower in high earthquake risk areas. They also show that the rents of houses built before 1981 - the amendment year of the Building Standard Law - are marked down more substantially than for houses built after 1981 in high-risk areas. Hidano *et al.* (2015) adopt a spatial two-dimensional regression discontinuity (RD) design to study the impact of information on seismic hazard risk on Tokyo's property market. They demonstrate that price premium in low-risk zones varies by the type of seismic hazard risk (the integrated seismic hazard risk, IR, and the risk of building collapse, BCR). Moreover, they show that the prices of newly constructed apartments are not significantly affected by the information on seismic hazard risk. Although the seismic hazard index in Japan, such as the ones used by the Japanese studies above, is more comprehensive by including several types of indices, it makes the identification of the impact of a particular hazard index difficult for the likely correlation between indices. The 2010-2011 liquefaction triggering earthquake sequence and the subsequent liquefaction hazard land zoning in Christchurch, on the contrary, provides a unique setting that enables the study of market response to a specific seismic hazard.

This paper also contributes to a large body of earthquake event studies on risk perceptions, risk salience, and housing values. Beron *et al.* (1997) analyze the impact of 1989 Loma Prieta Earthquakes on residential housing prices in the San Francisco Bay area using the expected loss from earthquakes as a measure of perception of risk in addition to SSZ in the hedonic price model. Moreover, soil type indices, susceptibility to ground shaking indices, and SSZ are used to predict the expected loss from earthquakes. Their results indicate that the hazard indices have significantly positive impacts on expected loss, hence significant negative impacts on housing prices before and after the 1989 earthquakes. Their results also point to a downward adjustment of perception of risk in the period after the Loma Prieta earthquake. Naoi *et al.* (2009) use nationwide data from Japan from 2004 to 2007 to analyze the hedonic price of perception of earthquake risk (probability seismic hazard) and the change in its effects before and after large earthquakes. They find that the price discounts in earthquake-prone areas become more significant after the actual earthquake events than before. The authors also find insignificant price discounts from locating in earthquake-prone areas before massive quakes, suggesting that earthquake risk was either unaware or underestimated before large quakes. In this paper, I also find that the liquefaction hazard in Christchurch was not taken into account before the 2010-2011 earthquake sequence, even with the existence of liquefaction hazard maps from a multi-stage liquefaction study.

Closely related to this paper, Logan (2017) uses a DID framework to examine the change in risk perception related to liquefaction on price differentials in the housing market between February 2007 and October 2012. He controls for the short-run earthquake effects (Sep 2010 and Feb 2011 quakes) and finds that after the 22 February 2011 Canterbury earthquake there was a price premium of 15.1, 18.8 and 16.1% to live in no risk, low risk and medium risk land, respectively, compared to high risk zoned land. Since the two earthquakes occurred only six months apart, assuming the impact of the first earthquake disappeared by the time of the second is likely to lead to an overestimate of the second earthquake impact. He uses the pre-earthquake liquefaction hazard map as the base for risk perception while comparing it to the post-earthquake TC map. Contrarily, I find that the hazard information provided in the pre-existing 2002 and 2005 liquefaction hazard maps was not accounted for in the property market before the 2010-2011 earthquake sequence. Hence, I estimate the impact of the post-earthquake liquefaction hazard zoning directly, controlling for the long-run earthquake impacts of the three liquefaction triggering quakes before hazard zoning.

For risk salience, Keskin and Watkins (2017) use a multi-level approach that allows for spatial submarkets within an event study framework to model changes in the pattern of house prices in Istanbul before (in 2007) and after (in 2012) the earthquake activity in Eastern Turkey in 2011. They find that the 2011 earthquake in the Van region had differential effects on the perceived risk of damage, which in turn form heterogeneous price discounts in 5 submarkets from the most expensive areas (submarket 1) to the cheapest areas (submarket 5). They show that submarkets at the cheaper end of the market have more significant price discounts. Fekrazad (2019) studies the house price in California from 1997 - 2016 to worldwide earthquake occurrences within the 20 years and finds short-living (one month) negative impacts of high causality earthquakes outside of California on house value index and median listing price in zip codes with high seismic activity. Timar *et al.* (2018) compare property prices before and after the 2010-2011 Canterbury and Christchurch earthquakes in two urban areas (one high, one low seismicity) outside of the Canterbury region to estimate changes in price premium to soil liquefaction potential, the previously largely ignored earthquake hazard. The only price discount they find is to liquefaction risk in the high seismic area, which disappeared within four years after the Canterbury earthquakes. For Christchurch, I find that the price discount due to liquefaction zoning in the most hazard-prone zone (TC3) is still as significant as 20% compared to the least hazard-prone zone (TC1), and 10% compared to the medium hazard-prone zone (TC2) in 2018, which is more than seven years after the land zoning and the earthquake sequence.

There are two more event studies of the 2010-2011 Canterbury earthquake sequence on housing sales patterns. Staer and LaCour-Little (2016) estimate a simple hedonic price model with time dummies to study the house sales prices before and after the 2010-2011 Canterbury and Christchurch earthquakes. They use monthly transaction data from 2010 to 2012 in Christchurch and show increasing use of auction and rapid increase in house prices post-earthquakes. They utilize the delineation of Technical Categories (TCs) in their robustness check but do not obtain consistent estimates. They do not differentiate the impact of a supply contraction from demand effect as the result of risk assessment but mainly focus on the increased use of auction post-earthquake that leads to high prices. They mention that the price increase post-earthquake is likely due to supply contraction and increased demand from displaced families and a net influx of workers to help rebuild the city. Bond and Dermisi (2017) examine sales price patterns before and after the 2010 September and 2011 February Canterbury and Christchurch earthquakes, from September 2008 to June 2012, using average trend analysis, GIS hot-spot analysis, and multiple hedonic regressions. They find that on average sales price increased in TC1 and TC2 (relatively lower liquefaction potential areas) in post-quake periods compared to TC3. However, they find prices in one of the TC1, and one of the TC2 decreased relative to TC3 post the 2011 earthquake. They estimate four hedonic regression (before Sep 2010 earthquake, after Sep 2010 earthquake, before Feb 2011 earthquake, and after Feb 2011 earthquake) for the overall area (controlling for TCs) and for each TC. In this paper, I use a quasi-experimental design to estimate a single hedonic model that accounts for not only earthquake-induced differential liquefaction effects but also the liquefaction land zoning effects.

In summary, the existing earthquake hazard literature finds that hazard disclosure in terms of earthquake or fault zone leads to price discounts in or close to the delineated zones; disclosure of hazard risks in terms of types of earthquake hazard leads to price discounts in more riskier areas. In addition, the actual earthquake event is found to change the risk or damage perception and increase the price discount in risk-prone areas in the earthquake region and found to have short-run price discounts in high seismic activity areas outside of the region struck by earthquakes.

The next section proposes the hypotheses and the theoretical framework in detail.

1.4 Hypotheses and Theoretical Framework

It is important to investigate how the local property market responds to hazard information before and after catastrophic events to find the efficacy of the hazard information for future policy designs. Moreover, in a country with a high level of earthquake insurance like New Zealand, knowing how the property market responds to earthquake-induced area-wide hazard assessment is essential for insurance design to mitigate the risk and cost of future earthquakes.

Unlike Logan (2017), which studies the change in risk perception to land liquefaction hazard defined as change from the pre-earthquake liquefaction classification to the post-earthquake TCs, the principal objective of the paper is to investigate the direct impact of TCs on property values. The first hypothesis to test is that the liquefaction hazard was not capitalized into property values before the 2010-2011 earthquake sequence. Although the liquefaction hazard was highlighted during the 2010-2011 earthquake sequence, earthquake-induced liquefaction and lateral spreading have long been recognized as potential hazards for some areas of Christchurch. As pointed out by Logan (2017), the pre-purchase Land Information Memorandum (LIM) well documented the liquefaction risk before the 2010-2011 earthquakes. A LIM is a comprehensive Council report that sets out all property information and any known hazards, including liquefaction risk, for the property whose records are kept by the Council. Moreover, Environment Canterbury (ECan) published liquefaction hazard maps for Christchurch in a five-stage study undertaken by Beca Carter Hollings & Ferner Ltd from 2001 to 2005. However, individuals were not required to request LIM before purchase, nor could they easily tell how susceptible their land was to liquefaction hazard from the liquefaction maps. Besides, since the 1990s, the government-owned Earthquake Commission (EQC) has been automatically providing equal amount of capped natural disaster insurance (EQCover) for all residential properties in New Zealand that have fire insurance from private insurance companies irrespective of its location, risk and size, with a capped NZ$100,000 (US$67,060) to building damage and a capped NZ$20,000 (US$13,412) to contents damage. Under this scheme, property owners pay a flat rate of 5 cents per NZ$100 (about an annual cost of NZ$69, including GST). Any over-cap coverage can be purchased from the private sector. According to Nguyen and Noy (2019), fire insurance is required for home loans so that more than 90% of residential properties in New Zealand are covered. Hence, I hypothesize that the liquefaction hazard was not taken into account for housing purchases and not capitalized into property prices in Christchurch before the 2010-2011 earthquake sequence. I will test this hypothesis using the liquefaction hazard maps from stage II (2002) and stage IV (2005) studies.

Acknowledging the first hypothesis that the property market did not account for the liquefaction hazard before 2010, I propose the main hypothesis that as the salience of liquefaction hazard and damage was heightened by the earthquake sequence the market took TCs instead of the change in hazard classifications into consideration. TCs outline the risk and damage from future liquefaction using land and property damages accrued from the 2010-2011 earthquake sequence, and the public can easily find out the TC of any property by searching the property's address on the provided website. Although potential sellers are not responsible for disclosing information on TC to potential buyers, government agencies, including EQC, urge the public to perform due diligence before selling or buying. The

2010-2011 earthquake sequence not only put liquefaction in the public spotlight but also required insurance and lending industries to review their policies. The EQC increased its flat-rate levy from 5 to 10 cents per NZ$100 (an annual cost of NZ$207 including GST) on February 1, 2012, and furtherer increased the rate to 20 cents per NZ$100 (an annual cost of NZ$276 including GST) on November 1, 2017. Starting from July 1, 2019, the EQC increased its coverage for building damage from NZ$100,000 to NZ$150,000 and withdrew contents coverage. The EQC pricing is still not risk-based; yet, many private insurance companies have been moving towards more risk-based pricing. Besides, according to Advanced Mortgage Solutions, although lenders are asking for the EQC documents regarding property's earthquake-damage assessment and the repair status for all properties purchased in Christchurch regardless of TC, more information is required for lending in TC3 properties. Hence, it is reasonable that the public would consider TCs instead of the change of hazard classification for house purchases after the 2011-2011 earthquake sequence.

The hazard literature has suggested a decrease in utility from a particular land parcel on which damages accrued from the natural hazard. How liquefaction hazard affects property prices can be illustrated through a simple expected utility model.

Following Brookshire *et al.* (1985), I assume that individuals account for the relative liquefaction hazard that classified as l and maximize expected utility from house consumption over two states, earthquake state with probability π, and no earthquake state with probability $1-\pi$:

$$V = \pi U_e[W - p(a,l) - l] + (1-\pi)U_{ne}[W - p(a,l)] \tag{1.1}$$

V is the expected utility; U is the continuous and twice differentiable utility that depends on the wealth level W and the price of house $p(a,l)$. The price of house depends on a vector of the structural and location attributes a and the land liquefaction hazard attribute l. $p(a,l)$ is also twice continuously differentiable. In the earthquake state, earthquake-induced liquefaction also causes an actual loss l. The subscripts e and ne stand for earthquake and no earthquake states. U is also assumed to decrease with liquefaction hazard. Although the Loma Prieta earthquake revealed that $1-\pi$ changed over time, simplifying it as time-independent would not change the sign of prediction below.

The utility-maximizing choice of hazard attribute l is then characterized by:

$$\frac{U_e'}{U_{ne}'} = -\frac{(1-\pi)p_l'}{\pi(1_l + p_l')} \tag{1.2}$$

$$p_l' = -\frac{\pi U_e'}{\pi U_e' + (1-\pi)U_{ne}'} < 0 \tag{1.3}$$

Equations (1.2) and (1.3) imply that the ratio of the marginal utilities of the earthquake and no earthquake states is equal to the ratio of marginal prices of the liquefaction hazard weighted by the probability of the two states. Further, the liquefaction hazard (as shown in equation 1.3) is negatively priced (i.e., as the level of liquefaction hazard increases, the price decreases). Therefore, I expect that as individuals gained information on the area-wide liquefaction hazard assessment when TCs were announced, utility from the more hazard-prone land (TC3 and TC2) would decrease and be manifested in depressed property values. Since TC3 is the most hazard-prone zone, property values in TC3 are expected to decrease more significantly. In TC1, where liquefaction hazard is unlikely, l in equation (1.1) approaches to 0 so that characterized in equation (1.3) also approaches 0. Hence, TC1 would be used as the reference category in the empirical analysis.

Left out of the above framework is the change in housing demand and supply over time as the result of the 2010-2011 earthquake sequence in Christchurch. The estimated loss of residential housing stock in Christchurch was around 5% (8,000 houses); to put this into perspective, there had been about 2,000 new residential buildings added to Christchurch's housing stock every year since 2003 to 2007 and a loss of 8,000 houses amounted to 4 years of the city's housing supply. The 2018 Stats NZ report showed that in the two years since June 2010, Christchurch's population had declined by about 20,000 people (5% of its usual population). Housing supply statistics from Christchurch City Council show that 20,100 new residential buildings were built between 2011 and 2018, among which 13,600 were net new residential buildings and 6,500 were replacement houses; the majority of new house construction (an annual average of 64%) took place in greenfield areas of the city. The statistics also show that the construction boom took off in 2013, with more than 3,000 new houses built every year since 2014; the current housing stock is higher than the pre-earthquake level. Also, according to Stats NZ's 2018 report, Christchurch's population returned to the pre-earthquake level in 2017. Altogether, there was evidence that housing pressure increased in Christchurch post-earthquakes at least until 2012.

1.5 Data

1.5.1 Housing Sales Data

Monthly unit record 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 the City of

Christchurch and covers the period from January 2000 to December 2018.

Basic QV data includes selling price, sales date, property address, floor area, land area, and various structural characteristics, along with the view and hazard information (e.g., inside/outside historical flood zone[8] and distance to the Christchurch coast). The analysis is targeted to all types of houses but not apartments. In total, there are 250,726 observations. Dropping observations with incomplete information on selling price, land or floor areas, structural characteristics, view, earthquake, flood and tsunami hazards, and observations with construction period longer than the selling year results in 117,154 transactions from 59,281 unique properties. An examination of the data reveals that sales price, land area, floor area, number of bedrooms, number of bathrooms, and number of carparks are all skewed to the right. Hence, each year, the outliers are dropped using the following process. First, the bottom 1% and the top 3% of sales prices were dropped. Then, the bottom and top 1% of the land was trimmed, followed by dropping the bottom and top 1% of floor areas. A further filtering step was taken to drop observations with the number of bathrooms, the number of bedrooms, and the number of carparks that are in the top 1%, respectively. At the end of the trimming process, the sample reduces to 107,486 observations from 55,046 unique properties.

1.5.2 MBIE Technical Categories

In addition to the property hazard information provided in the QV dataset, MBIE technical categories (TCs) for foundation systems supplied by CERA are also used. To assign the technical category (TC) to each of the 55,046 unique properties, the following procedures

[8] 99.82% of the observations are inside the historical flood zone in the final analytical sample. Hence, flood zone hazard is neither reported in the summary statistics nor used in the empirical analysis.

are taken.

Land Information New Zealand (LINZ) is the government department responsible for managing land titles, geodetic and cadastral survey systems, topographic, and information as well as Crown property. LINZ's Address Information Management System (AIMS) contains information on address position, address ID, parcel ID, and components of each address such as address number, street number and road name that can be combined into single full addresses and linked to the housing address in the QV. At the end of this step, 54,635 unique properties (106,760 observations) have their address positions found in AIMS. Then, the rest of the 411 unique properties (726 observations) have their addresses geocoded in R and overlaid to the map of New Zealand Primary Land Parcels downloaded using LINZ Data service. The geocoded addresses that fall on a road had their positions hand-corrected. Next, all the addresses are overlaid to the MBIE Technical Categories Land Zoning map that assigns the flat residential land (CERA Green Zone) one of the three TCs (TC1, TC2, and TC3) on an area-wide basis. The MBIE TC map is accessed from ArcGIS online. In total, there are 8,852 unique properties (17,251 observations) in TC1 (gray), 27,774 unique properties (55,575 observations) in TC2 (yellow) and 9,300 unique properties (18,922 observations) in TC3 (blue). There are four additional zones provided in the MBIE map: residential red zone, urban nonresidential, rural and unmapped, and Port Hills and Banks Peninsula. 19 unique properties (28 observations) are in the residential red zone. 2,265 unique properties (4,025 observations) are in the urban nonresidential areas, and 2,070 unique properties (3,535 observations) are in the rural and unmapped areas. 98% of the transactions in the urban nonresidential and rural unmapped areas occurred after the 2010 September earthquake. 4,763 unique properties (8,147 observations) are in Port Hills and Bank Peninsula, where land is significantly elevated due to the hilly and mountainous features. Hence, to complete, the 9,098 unique properties (15,707 observations) that fall outside of the three technical categories and 19 unique properties (28 observations) that fall in residential red zone are dropped. The final sample contains 91,748 observations from 2000 to 2018.

A set of geographical distances is also calculated for each property. Distance from the Central Business District (CBD) is measured as straight-line kilometers (km) from a house to the boundary of the Cathedral Square census area unit.[9] Distance from each of the four types of parks (regional, botanical, community, and sports park) is kilometers from a house to the boundaries of the nearest park of each type. Distances from hospitals are kilometers from a house to the nearest public hospital and the nearest private hospital. Distance from the water is kilometers from a house to the boundary of the nearest water body (i.e., lagoon, lake, pond, reservoir, and river). Finally, the distance from the boundary of the nearest residential red zone is also computed for each house.

Summary statistics for the final analytical sample of 91,748 observations are shown in Table 1.1. The mean selling price from 2000 to 2018 is NZ$331,438, with an average floor area of 154.37 m^2 and a mean land area of 667.68 m^2. Houses sold in the 19 years are most likely to have been built in the 2000s (20%), 1960s (16%), 1950s (13%), and 1920s and 1970s (10% each). 89% of the properties have the typical design and an average to good quality of the era of construction.[10]

[9] Definition of Area Unit by Statistics New Zealand: area units are aggregations of the smallest census geographic area, meshblocks, in New Zealand. The median size of area units is 2,000 people, while three-quarters of area units have a population between 100 and 4,000.

[10] The purchased data provides a three-level quality code of the building: 1) Superior design and first-class quality of fixtures; 2) The design is typical of its era, and the quality of the fixtures is average to good; 3) The design is below the level generally expected for the era, or the level of fixtures is barely adequate

On average, houses are 4.6 km from the CBD, 7.08 km from the Christchurch coast, 3.84 km, and 5.05 km from the nearest public and private hospital, respectively, 1.40 km from the nearest water body, and 3.83 km from the nearest residential red zone. The mean distances from the nearest regional, botanic, community, and sports parks are about 2.48 km, 1.80 km, 0.21 km, and 0.40 km, respectively. Finally, 19%, 61%, and 21% of the observations are in TC1, TC2, and TC3, respectively.

1.6 Empirical Models and Results

1.6.1 Liquefaction Hazard Before 2010-2011 Earthquake Sequence

A possible concern is that the liquefaction hazard was captured in the property market even before its massive manifestation in the 2010-2011 earthquakes. After all, the 2001-2005 Christchurch multi-stage liquefaction study was conducted to evaluate the long-recognized potential liquefaction hazard. If this were the case, the market would have updated its perception of the hazard when TCs were announced, and it would have been the changes in risk classification rather than TCs that mattered. Hence, I start by testing the first hypothesis on market response to the liquefaction hazard before the 2010-2011 earthquake sequence using the 2002 and 2005 hazard maps from the 2001–2005 five-stage study. The 2002 and 2005 liquefaction hazard maps can be found in the ECan report of the same year. The ECan provided the shapefile of the 2005 hazard map; the 2002 hazard map was first digitized from the 2002 stage II report, and then geo-referenced and converted to a shapefile

and possibly of below-average quality.

in ArcGIS.

The 2002 liquefaction hazard map is shown in Figure 1.3, which covers a smaller area than the TC map in Figure 1.2. It provides three risk classes: high, moderate, and low. The straight-line distance from the boundary of the nearest risk class was calculated for each house. If a house falls in a risk class, its distance to that risk class would be 0; a house is then assigned the risk class into which it falls.

To verify whether the potential liquefaction hazard presented by the 2002 study map was priced in the property market, I run the following hedonic model for the period 2000 to 2005 that covers three years before and after the study:

$$
\begin{aligned}
log(P_{igt}) = \sum_{g=2}^{3} \delta_g * Risk_g + \gamma * post2002 + \sum_{g=2}^{3} \lambda_g * (Risk_g \times post2002) \\
+ X'_{igt} * \alpha + Z'_{igt} * \beta + \rho_t + \phi_s + \mu_{au} + \varepsilon_{igt} \qquad (1.4) \\
i = 1, \cdots, N, \quad \varepsilon_i \sim N(0, \sigma_i^2)
\end{aligned}
$$

The dependent variable $log(P_{igt})$ is the log of the selling price of house i in group g in year t. The independent variables to test are the risk classes ($Risk_g$) post-2002, whose effects are measured by λ_g. I control for property characteristics (X_{igt}), proximities to amenities (Z_{igt}, I allow for nonlinearity), year fixed effects (ρ_t), seasonal fixed effects (ϕ_s) and area unit fixed effects (μ_{au}). Estimates in Appendix Table A.1 suggest that property values did not respond to the 2002 liquefaction hazard classes.

Figures 1.4a and 1.4b present the liquefaction hazard maps based on the summer and winter groundwater levels, respectively, from the 2005 study. Both maps provide more risk classes than the 2002 hazard map. Again, the straight-line distance from the boundary of the nearest risk class was created for each house in both summer and winter schemes, and distance to a risk class would be 0 if a house falls in the area of that risk class. I also create a joint map by combining the summer and winter maps in the way that each site was assigned the risker class of the two, as shown in Figure 1.4c, with each house is then assigned the risk class into which it falls.

To verify whether the potential liquefaction hazard assessed and updated in the 2005 study was capitalized in the property market, I run the following hedonic model for the period 2003 to 2008 that covers three years before and after the study:

$$\begin{aligned} log(P_{igt}) = \sum_{g=2}^{6} \delta_g * Risk_g + \gamma * post2005 + \sum_{g=2}^{6} \lambda_g * (Risk_g \times post2005) \\ + X'_{igt} * \alpha + Z'_{igt} * \beta + \rho_t + \phi_s + \mu_{au} + \varepsilon_{igt} \qquad (1.5) \\ i = 1, \cdots, N, \quad \varepsilon_i \sim N(0, \sigma_i^2) \end{aligned}$$

The independent variables to test are the risk classes from 2005 study ($Risk_g$) post-2005, the effects of which are measured by λ_g. Estimates in Appendix Table A.2 suggest that property values did not respond to the 2005 liquefaction hazard classifications in a meaningful way. Altogether, the results of these two pre-earthquake tests suggest that liquefaction hazard was not previously capitalized in the property market, indicating that the public either was not aware of the hazard or did not care about the hazard.

1.6.2 Long-run Impacts of TCs - Baseline DID Models

The main objective of this paper is to identify the impact of the assessed liquefaction hazard classified by land's Technical Categories (TCs) on property prices. The pre-earthquake tests show that property prices did not differ by potential liquefaction hazard before the

2010-2011 earthquake sequence, suggesting the absence of pre-existing risk perception to liquefaction hazard. Once liquefaction caused wide-spread damage and gained sharp attention during the earthquake sequence, it is reasonable to assume the market responded to the TCs that was announced immediately after the earthquake sequence instead of the change in risk compared to the pre-existing classification.

Hereafter, transactions from 2005 to 2018 are used to examine the effects of TC zoning. It spans seven years before and after the TC announcement. In Figure 1.5, the three TCs exhibit similar pre-trends before TC announcement, suggesting that DID can be used to provide causal estimates of the impact of TC zoning.

TCs were established mainly using information (including land and property damages and liquefactions) collected after the 2010-2011 earthquakes. Hence, a possible concern is that it is likely that the property market responds to the occurrence of severe earthquakes rather than the delineated land technical categories. To overcome the problem, timings of the three significant quakes that led to hazard assessment are also controlled for in addition to the timing of the TC announcement in the hedonic model below:

$$
\begin{aligned}
log(P_{igt}) = \sum_{g=2}^{3} \delta_g * TC_g + \sum_{e=1}^{4} \gamma_e * post_e + \sum_{g=2}^{3}\sum_{e=1}^{4} \lambda_{g,e} * (TC_g \times post_e) \\
+X'_{igt} * \alpha + Z'_{igt} * \beta + \rho_t + \phi_s + \mu_{au} + \varepsilon_{igt} \qquad (1.6) \\
i = 1, \cdots, N, \quad \varepsilon_i \sim N(0, \sigma_i^2)
\end{aligned}
$$

$post_e$ is an indicator for the transaction being occurred after event e. Four events included in this specification are earthquakes on September 4, 2010, February 22, 2011, and June 13, 2011, and the announcement of TCs on October 28, 2011.

Event	Impact Period	Indicator
EQ1	[Sep 04, 2010, -]	$post1 = 1$
EQ2	[Feb 22, 2011, -]	$post2 = 1$
EQ3	[Jun 13, 2011, -]	$post3 = 1$
TC	[Oct 28, 2011, -]	$post4 = 1$

With this specification, the impact of each earthquake is assumed to be constant and long-lasting to overcome the concern of delayed earthquake effects; the cumulative impacts of successive quakes are the sums of the individual impacts. The coefficients of interest are $\lambda_{g,e}$, which are the coefficients on indicators for TC_g interacted with $post_e$. As before, I control for property characteristics (X_{igt}), proximities to amenities (Z_{igt}), year fixed effects (ρ_t), seasonal fixed effects (ϕ_s), and area unit fixed effects (μ_{au}). I also estimate the above model with distance to the nearest residential red zone (area with significant and extensive liquefaction damage and not habitable in the near future) and its interactions with TC_g and $post_4$. Properties in the residential red zones were demolished over the years. Up to 2018, some parts of the red zones were reverted to swampland, and others became vacant land with unruly vegetation. Interacting TC with distance to the red zone allows for heterogeneous effects of TC zoning to the possible loss of amenity in red zones or the high liquefaction risk potential being closer to the red zones.

Column (1) of Table 1.2 presents the baseline specification denoted by equation (1.6). Estimates show that the 2010 September earthquake and the devastating 2011 February earthquake, the first two in the sequence, caused area-wide adverse effects on property values, though not statistically significant. The succeeding significant aftershock in June 2011 depressed prices in TC3 by 8.1% compare to TC1 and TC2. This suggests that as massive liquefaction was observed after the three liquefaction triggering quakes, the market had obtained some knowledge to distinguish the severity of liquefaction hazard of at least some places later zoned as TC3; yet, at this stage, the market had not enough information to assess the risk in the rest of the city. Once the TCs were established and announced on October 28, 2011, it clarified the hazard information to the public which was not apparent before and reduced prices in TC2 and TC3 by 7.4% and 21.8% compared to TC1 respectively, suggesting that the informative TCs not only introduced price discounts in TC2 but also enhanced price discount in TC3. Being classified TC3 caused prices to decrease by 14.4% ($t = -4.15$) compared to TC2; this confirms the hypothesis that as the earthquake sequence heightened the salience of liquefaction hazard and the resulted TC zoning, house prices in TC3, the most hazard-prone area, decreased significantly. Caution must be taken to interpret the results. The most liquefaction hazard-prone area, TC3, may have also suffered most from property loss that could result in a contraction in house supply. However, supply contraction, *ceteris paribus*, would result in an increase in price. That is, if the counteractive supply factor is present in TC3, the estimated 21.8% decrease in price in TC3 would be an underestimate of the average impact of hazard zoning in TC3. Additionally, with this empirical specification, the effect of each earthquake never goes away; hence, for this reason, the estimated average impacts of TC zoning are also underestimated.

In column (2), I include distance to the boundary of the nearest residential red zone (the extensively and severely liquefied area that are not habitable in the near future) and its interaction terms with TCs after TC zoning, which increased the R-squared slightly from 61.2 to 61.6 percent. After including these additional distances to red zone controls, the impacts of the earthquakes were not affected. However, the differences across TCs before the first earthquake disappeared, suggesting that distance to residential red zones is an important determinant of the spatial equilibrium. The 2010 September and the 2011 February earthquakes still appeared to have no significant effects, while the June aftershock depressed property prices in TC3 by 8.8%. Once the TCs were introduced, property prices dropped by 3.9% (not statistically significant) and 20.8% in TC2 and TC3, respectively, comparing to TC1. Being classified TC3 caused prices to decrease by 16.9% ($t = -4.66$) compared to TC2. These results verify that the repeated liquefaction that occurred in the earthquake sequence changed the price structure slightly, and the area-wide TC zoning helped the market to reinforce the structure of change to the levels of liquefaction hazard. Regarding distance to the residential red zones, estimation results in column (2) show that property values increased with distance to the residential red areas most in TC3 after the earthquake sequence. This suggests that not only the effects of TC zoning are not fixed in space, but also the change in the price structure also occurred due to the loss of amenity in red zones or higher risk perceived be closer to red zones.

Altogether, estimation results in columns (1) and (2) of Table 1.2 provide evidence that the market had acquired some knowledge on the severity of liquefaction hazard in at least some areas later classified as TC3 by the third quake and the earthquake sequence had triggered a structural change to the hazard. After the levels of hazard were clarified on an area-wide scale as TCs, it reinforced the structural change; property values in the most hazard-prone TC (TC3) dropped the most. Moreover, price discounts also occurred in terms of proximity to the residential red zones. Furthermore, the price impact of TC zoning is not fixed in space; houses closer to residential red zones are penalized more within each TC; this proximity penalty is the largest in TC3.[11]

1.6.3 Dynamic Effects of TCs - Event Study

The hazard zoning is time-invariant, yet the effects of the zoning might change over time. Hence, this section presents an event study analysis that examines the dynamic effects of liquefaction hazard zoning by comparing houses in TC2 and TC3 to houses in TC1. The following regression is estimated, where r indexes the year relative to the TC announcement date:

$$\begin{gathered} log(P_{igt}) = \sum_{g=2}^{3} \delta_g * TC_g + \sum_{r=-7}^{7} \gamma_r + \sum_{g=2}^{3} \sum_{r=-7}^{7} \lambda_{g,r} \\ + X'_{igt} * \alpha + Z'_{igt} * \beta + \rho_t + \phi_s + \mu_{au} + \varepsilon_{igt} \qquad (1.7) \\ i = 1, \cdots, N, \quad \varepsilon_i \sim N(0, \sigma_i^2) \end{gathered}$$

In the above equation, TC_g is an indicator for being in technical category g, γ_r represents coefficients on indicators for year relative to TC announcement date, and $\lambda_{g,r}$ are the coefficients on indicators for the interactions between technical category g and relative year r. TCs were announced on October 28, 2011; hence, $r = -1$ corresponds to October 28, 2010 - October 27, 2011, and so forth (Appendix Table A.3). In total, the analytical data covering 2005 to 2018 ranges from -7 years to 7 years to the introduction of TCs. In the analysis, two years before the TC announcement ($r = -2$: Oct 28, 2009 – Oct 27, 2010) is set as the reference time to avoid the potential negative impacts caused by the 2010 September earthquake. Although the first earthquake struck on Sep 4, 2010, Oct 28, 2009 - Oct 27, 2010 still largely

[11] A discussion of structural and amenity controls is presented in Appendix section A.3.

represents the time immediately before the earthquake sequence and property price in this period is arguably the pre-earthquake price. Again, I control for property characteristics (X_{igt}), proximities to amenities (Z_{igt}), year fixed effects (ρ_t), seasonal fixed effects (ϕ_s), and area unit fixed effects (μ_{au}). I also estimate the above model with distance to the nearest residential red zone and its interactions with $\boldsymbol{TC_g}$ and γ_r.

Figure 1.6a plots the estimated dynamic impacts of TCs ($\lambda_{g.r}$) without controlling for distance to the red zones, while column (1) of Table 1.3 reports the estimates. Within the year TC was announced, relative sales price in TC3 decreased by 15.9%; up to the third year, the price level in TC3 had dropped by 38.3% relative to TC1. By the end of 2018, the price discount due to TC zoning is still as substantial as 20.7% in TC3 compared to TC1 and TC2. On the other hand, zoning introduced a milder effect, about -6%, in TC2 since the second year of zoning; the effect due to zoning almost disappeared by the end of 2018. Dynamic TC effects with distance to the red zones are plotted in Figure 1.6b, which are in similar magnitudes to results in Figure 1.6a. Corresponding estimates are presented in column (2) of Table 1.3. Structural change in distance to the red zone can be seen in Figure 1.6c. This proximity penalty is the largest in TC3; at its most significant, the price penalty in TC3 is about 5.8% per kilometer closer to the residential red zone. Results in this section not only confirm a long-lasting change in area-wide price structure due to hazard classification but also show that the effects of hazard zoning get muted three years after zoning. Even with the zoning effects getting smaller over time, it took seven years for the price differential between TC2 and TC1 to disappear. Moreover, the average price in TC3 was still about 20% lower compared to TC1 seven years after zoning.

1.6.4 Robustness Analysis

In this section, I test the robustness of the impacts of the liquefaction hazard zoning to various specification changes.

1.6.4.1 Falsified Technical Categories and Zoning Dates

First, I perform two placebo tests by re-estimating the baseline model with falsified technical categories and falsified zoning date, respectively. The 2005 liquefaction hazard classes are used as the base to form the "falsified" TCs. First, the six liquefaction hazard classes are grouped into three classes as follows: high and high-uncertain are grouped as "high", moderate and moderated-uncertain are grouped as "moderate", low and low-uncertain are grouped as "low". Next, each property is assigned one of the three risk classes it falls in. The 2005 liquefaction hazard map barely encompass TC1, and 92% of properties in TC3 are in the moderate and high classes. Hence, I created the three "falsified" TCs (high, moderate, low) only using properties in TC2. In the end, 23.15% of observations are in the "low" class, 31.36% are in the "moderate" class, and 45.49% are in the "high" class. Evidence that prices differed by the "falsified" TCs after the actual TC announcement date would indicate that the market responded to the change in risk classification instead of the real TCs as the "falsified" TCs are all created from TC2 and invalidate my main results. Placebo test two excludes transactions after September 2010. In the pre-earthquake period January 2005 to August 2010, the "falsified" TC announcement date was set in the middle, on October 1, 2007. Placebo test two is also tested using transactions between 2005 and 2007, with June 1, 2006, being the "falsified" TC announcement date, to avoid the possible confounding effects caused by the global financial crisis. Evidence that relative prices changed after the "falsified" zoning date would indicate that the design of TCs might be correlated to some unobserved factors that also affect underlying price formation over time. Results of placebo test one, presented in panel A of Table 1.4, show that neither the earthquakes nor the falsified TCs had significantly differential effects on relative prices, which confirms that the market responded to the actual TCs instead of the change in the hazard categories. Results of placebo test two, shown in panel B of Table 1.4, suggest that price differentials among TCs after the TC delineation were not driven by the unobserved differences in underlying price formation across the TCs.

1.6.4.2 Spatial Conditionally Parametric - Semiparametric Models

Spatial data, especially spatial housing data, is well acknowledged to display spatial heterogeneity usually. The standard parametric hedonic regression denoted in equation (1.6) employs area unit fixed effects to control for spatial variation in housing prices. A drawback of the standard hedonic approach is that housing prices would change discretely over space. Moreover, the standard hedonic price function is likely to be subject to model misspecification, even if polynomial terms of land and floor areas and distances to amenities are used in equation (1.6). To allow property prices to vary smoothly over space, I use the combination of conditionally parametric regression (CPAR) model proposed by McMillen (1996) and semiparametric (SemiP) model by Robinson (1988).

The general CPAR model has the following form:

$$y_i = \alpha(longitude_i, latitude_i) + \beta(longitude_i, latitude_i)' X_i + \varepsilon_i$$

where the location of house i denoted by its geographical coordinates longitude and latitude enters fully nonparametrically, and the vector of X_i enters conditionally parametrically.

With CPAR, at any given pair of longitude and latitude, the model is the standard linear regression, yet coefficients of X vary with longitude and latitude. A kernel weight function, including only geographical coordinates, defines distances between houses and assigns higher weights to nearby houses.

The general Semip model is similar to the CPAR in that some variables, say longitude and latitude, are fully nonparametric; but differs from the CPAR model by constraining other variables to be fully parametric so that they do not vary with longitude and latitude:

$$y_i = \alpha(longitude_i, latitude_i) + \beta' X_i + \varepsilon_i$$

Using the combination of the CPAR model and SemiP model, I estimate the following function:

$$\begin{aligned} log(P_{igt}) = \sum_{g=2}^{3} \delta_g * TC_g + \sum_{e=1}^{4} \gamma_e * post_e + \sum_{g=2}^{3} \sum_{e=1}^{4} \lambda_{g,e} * (TC_g \times post_e) \\ + X'_{igt} * \alpha_i + Z'_{igt} * \beta_i + \rho_t + \phi_s + \mu_{au} + \varepsilon_{igt} \qquad (1.8) \\ i = 1, \cdots, N, \quad \varepsilon_i \sim N(0, \sigma_i^2) \end{aligned}$$

Coefficients with the subscript i demonstrate that they are local (i.e., specific to house i) and vary smoothly over space. That is, property and amenity characteristics are conditionally parametric and vary with geographical coordinates. Post-event dummies, TCs, year and, seasonable variables enter fully parametrically to capture their average effects. As before, I also estimate the additional effect of proximity to the nearest residential red zone, which also enters the model fully parametrically.

The coefficients from the parametric part of the models with and without distance to the red zone are presented in columns (3) and (4) of Table 1.2, respectively. Both models are estimated at the window size of 30%[12] and using a tri-cubic kernel function $\frac{70}{81}(1-(|z|)^3)^3 * I(|z|<1)$.

Results are consistent and comparable in magnitudes with the standard hedonic results. The market had gained some knowledge to distinguish the most hazard-prone and least hazard-prone areas after the third quake in the sequence. Once the liquefaction hazard zoning, TC, was announced, it clarified the area-wide liquefaction hazard to the public and caused relative property prices to drop by 22 to 25.5% in TC3 and decrease by 8.2 to 9.1% in TC2. Results also confirm that property values increased with distance from the residential red zones most in TC3 and least in TC1 post-earthquakes.

As a whole, results from the spatial models affirm the results from the standard hedonic models. The earthquake sequence prompted the market to experience a structural change from the impacts of the wide-spread liquefaction. Although hazard zoning is due to extensive liquefaction triggered by the long-lasting earthquake sequence, it is the hazard zoning rather than the earthquake that clarified the hazard information across the city and underpinned the price differences across TCs. Furthermore, distance to residential red zone plays an important role in capturing the spatial equilibrium; a structural change in price also occurred post-earthquakes as a function of proximity to residential red zones in each of the TC possibly due to the loss of amenity or the perceived higher liquefaction risk closer to the red zones.

[12] McMillen and Redfearn (2010) suggest using a larger window size in nonparametric estimation when broad spatial effects such as distance from CBD are included in the model. They also show that the standard 20% - 50% window sizes do not use much degree of freedom.

1.6.4.3 Boundary Discontinuity

Another concern is that other structures, such as commercial buildings and schools, are also affected by liquefaction. Some might need to reallocate. This leads to a possible spatial change in local services. Moreover, the supply and demand for housing may change heterogeneously by the defined zones over time. As a result, the estimated hazard zoning effects should not be interpreted as due to TC zoning alone. To validate the main results, I adopt the boundary discontinuity design as an additional robustness check.

With boundary discontinuity design, houses within proximity to each other but on opposite sides of a geographical boundary are compared. This method assumes that neighborhoods change smoothly over space and requires that the boundary in question does not coincide with any main geographical features such as school attendance zones and tax zones. In the context of this paper, the boundaries of the TCs were the outcome of rigorous research by the Department of Building & Housing (DBH) based on historical and post-earthquake data, consultations with geotechnical, engineering and research groups. Hence, it is unlikely that TCs coincide with any main geographical features. If neighborhoods change continuously over space and time, by comparing houses very close to the boundaries, where there is a discrete change in TC classification at a given point, effects due to neighborhood-specific unobservable can be eliminated. Moreover, as Hidano *et al.* (2015) pointed out, the actual hazard level is likely to change continuously rather than sharply over space so that the actual change in hazard level should approach zero on the boundaries of hazard zones as should the property values if the public care only about the actual hazard levels. If a significant change in prices occurs on the boundaries after the boundaries were defined, it can only be that prices responded to the hazard classification.

To proceed, I first extracted the shared boundaries between TC2 and TC3 and between TC2 and TC1 (Figure 1.7). Then, houses that are within 100m of the shared boundaries were selected. Houses with no adjacent houses on the opposite side of the shared boundaries were dropped. I re-estimate equations (1.6) and (1.7) for houses that are within 100m from shared boundaries between TC2 and TC3 and houses that are within 100m from shared boundaries between TC2 and TC1.

Figure 1.8 shows the mean log of selling prices on the opposite side of shared boundaries. As displayed in Figure 1.8a, average prices did not change on the shared boundaries of TC2 and TC3 pre-zoning and average prices in TC3 decreased in the period after zoning relative to TC2. On the shared borders of TC1 and TC2, shown in Figure 1.8b, zoning did not appear to cause changes in price. The relevant descriptive statistics are shown in Appendix Tables A.5 and A.7.[13]

Estimates in panel A of Table 1.5 indicate that the difference in liquefaction hazard classification caused long-run average property prices to drop by about 9.7 - 14.5% in TC3 compared to TC2 (the differences are about 14.4 - 16.9% in columns 1 and 2 of Table 1.2 from the baseline DID models, respectively). Dynamic TC effects on the shared boundaries of TC2 and TC3 are plotted in Figure 1.9a, while Appendix Table A.6 reports the estimates; the hazard classification had been causing a price discount of more than 10% in TC3 relative

[13] Descriptive statistics in Appendix Tables A.5 and A.7 show that the covariates are not balanced across the shared boundaries. Although differences in some covariates are not economically significant, they are statistically significant. Hence, to improve the balance between covariates, I also use the nearest neighbor matching with a caliper width of 0.2 on the whole set of structural attributes used in this paper and restricting the sample to matched houses that are in the range of the common support. Descriptive statistics for the matched sample are presented in Appendix Tables A.9 and A.10. DID results obtained using the matched sample are presented in Appendix Table A.11 and are very similar to results without matching.

to TC2 since the second year of the zoning, and the price discount was still as significant as 10% seven years on in 2018. Figure 1.9b shows that there was an additional relative price discount in TC3 due to proximity to the residential red zones in the first three years post-zoning.

On the other hand, results from comparing houses within 100m of shared boundaries between TC2 and TC1 in panel (b) of Table 1.5 show that TC classification caused prices to decrease by about 6 - 8.8% in TC2 compared to TC1 (the differences are 3.9 - 7.4% in columns 1 and 2 of Table 1.2, respectively); yet, the difference is statistically insignificant (i.e., zoning did not introduce price effects on the shared borders of TC1 and TC2). Dynamic effects plotted in Figure 1.10 (corresponding estimates are presented in Appendix Table A.8) also confirm that there is no significant difference due to zoning on the shared borders of TC1 and TC2. The insignificant difference between TC2 and TC1 post-zoning is also likely to be due to the small sample size along the shared boundaries.

By and large, results in this section verify the main findings that the liquefaction hazard zoning denoted by TCs depressed prices the most in TC3. On average, being classified in the most hazard-prone caused property values to drop by about at least 10% compared to being classified as the second most hazard-prone.

1.6.4.4 Alternative Earthquake Impact Period Specification

The main specification defined in equation (1.6) assumes that the impacts of earthquakes never go away, which could lead to an underestimation of the impacts of hazard zoning. Hence, an alternative earthquake impact period is considered to allow the impacts of earthquakes to be transient.

Four event indicators are constructed from the four events as following:

Event	Impact Period	Indicator
EQ1	[Sep 04, 2010, Feb 22, 2011)	$e1 = 1$
EQ2	[Feb 22, 2011, Jun 13, 2011)	$e2 = 1$
EQ3	[Jun 13, 2011, Oct 28, 2011)	$e3 = 1$
TC	[Oct 28, 2011, -]	$e4 = 1$

With this modification, the impact of each earthquake is very short-lived and exists only before the occurrence of the next event. The problem with this modification is that since the earthquakes and hazard zoning are so closely spaced in time (six months apart at most), if the impacts of earthquakes last for more than half a year or are delayed, those impacts will be picked up by the TCs.

Estimation results are presented in Table 1.6 and are mostly consistent with the estimation results in Table 1.2 namely, that by the third quake, the market had gained some information about the liquefaction hazard in at least some of the most hazard-prone areas; the clarification through TCs enhanced the price discount in TC3. As expected, estimated TC effects are more significant (about 10% larger in TC3) than the baseline estimates, confirming that earthquake impacts are picked up by the TCs with this alternative specification. Hence, the TC effects in this section should be considered as the upper bound of the zoning effects.

1.7 Conclusion

This paper contributes to the understanding of hazard zoning and salience of hazard information. Specifically, I estimate the impacts of the earthquake-induced liquefaction hazard zoning on house prices in Christchurch, New Zealand. The actual level of liquefaction hazard may vary continuously and may not always be visible on the surface even after earthquakes. Technical Categories (TCs) provide easily accessible information regarding the degree of liquefaction damage hazard to the public. The timings of the earthquake sequence and the TC announcement help in estimating the average effects of hazard zoning on house prices that would otherwise be confounded with earthquake effects.

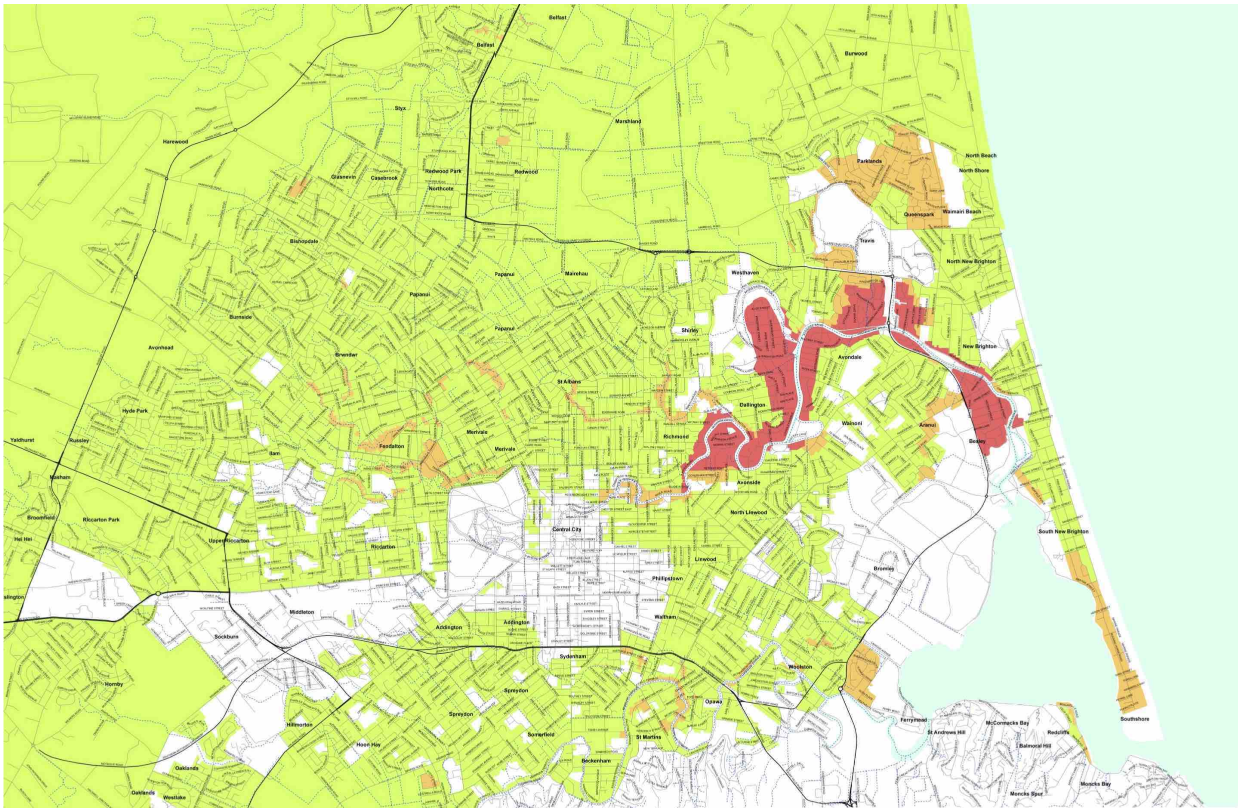
My analysis provides robust evidence that the liquefaction hazard was not priced in Christchurch before the 2010-2011 earthquake sequence, even though the inherent hazard had long been recognized. This is consistent with the finding of Naoi *et al.* (2009) in Japan that earthquake risk was not accounted for before massive quakes. The 2010-2011 earthquake sequence drew sharp attention and prompted the market to undergo a structural change to levels of liquefaction hazard; introduction of the TCs clarified levels of liquefaction hazard on an area-wide scale and enhanced price changes to severity of liquefaction hazard. After the introduction of TCs, property values decreased substantially in TC3 where moderate to significant liquefaction damage is likely in future earthquakes; being classified as the most hazard-prone (TC3) caused the long-run average price to decrease by at least 10% than being classified as the second most hazard-prone (TC2) and by 20% than being classified as the least hazard-prone (TC1). However, the long-run price reduction in TC2 is moderate compared to TC1, by about 7%.

My results also show the saliency of hazard information disclosed shortly after significant earthquakes. Price discounts in TC3 enlarged to almost 40% by the third-year post-zoning and dwindled afterward compared to TC1; yet, seven years on, the price discount is still as substantial as 20%. Price reduction in TC2 was relatively small by around 6% since the second year of zoning but almost vanished in the seventh year. Moreover, my results show that the 2010-2011 earthquake sequence also led to a negative structural change to proximity to residential red zones (areas that were too severely liquefied residential to be habitable); this is likely due to either the loss of amenity in red zones or the perceived higher risk in proximity to red zones after earthquakes. Furthermore, my results provide a new piece of evidence to the literature by showing that with fragmented hazard zones, zoning effects are not fixed in space; relative price decreased most for being in the most-hazard prone zone (TC3) and being close to the inhabitable area (residential red zone) resulted from the earthquake sequence. Additional research is required to account for the possible spatial spillover effects across the hazard zones.

My findings for the impacts of hazard zoning in Christchurch provide valuable insights into long-term disaster management. According to the psychological theory and evidence, people have limited attention to the information in an information-rich environment. If people do not pay attention to the hazard information disclosed (usually in the disaster quiet time), hazard disclosure will be found to be ineffective. Costly natural disasters such as hurricanes and earthquakes draw people's attention to the hazards induced by the events and make either the exiting hazard information (e.g., see Bin and Landry, 2013 for hurricane-induced differential effects inside and outside the flood zones) or the disaster-induced hazard information disclosure (e.g., earthquake-induced liquefaction zoning as shown in this paper), more salient. My findings also provide a lower bound of price response to hazard zoning in the global setting. New Zealand has a high level of residential earthquake insurance penetration, more than 90%, while the residential earthquake insurance take-up rate in California is only around 10%. If the earthquake sequence and the resulted liquefaction zoning were in California, the expected loss to homeowners, and the price response to hazard zoning would have been a lot larger.

1.8 Figures and Tables

Figure 1.1: CERA Land Information Map



Source: Canterbury Earthquake Recovery Authority (CERA) and author's modifications

Note: This map was announced on June 23, 2011.

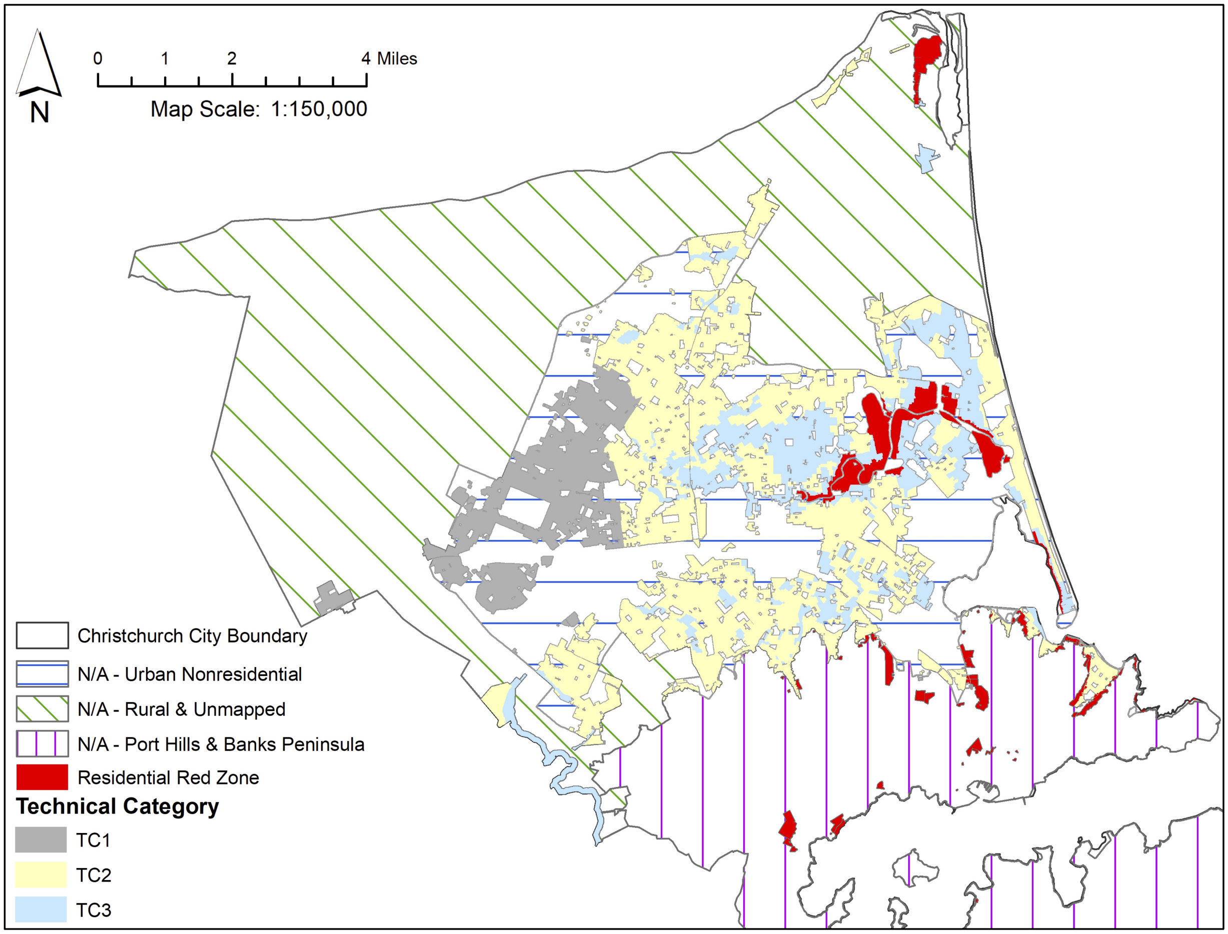
Red – land not recommended for continued residential development in the short term;

Orange – land needed further investigation;

Green – land suitable for repairing and rebuilding homes on;

White – Port Hills and the central city.

Figure 1.2: MBIE Residential Foundation Technical Categories



Note: This map was published on October 28, 2011, and accessed from ArcGIS online. Source: Canterbury Earthquake Recovery Authority (CERA) and author's modifications

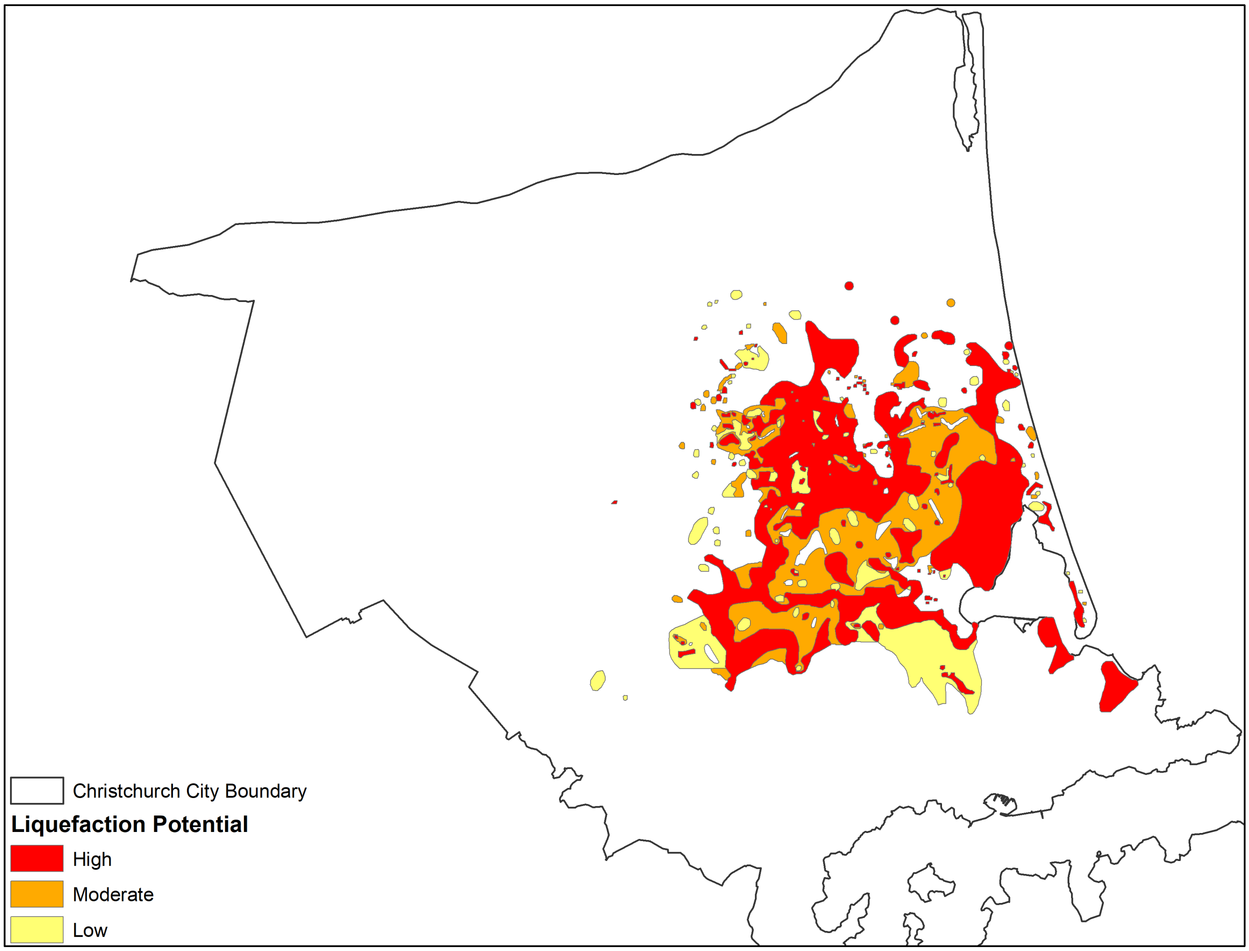
TC1 – future land damage from liquefaction is unlikely so that standard residential foundation assessment and construction is appropriate;

TC2 - minor to moderate liquefaction damage to the land is possible in future large earthquakes so that shallow ground investigations may be required when repairing or replacing foundations;

TC3 - moderate to severe liquefaction damage to the land is possible in future large earthquakes so that geotechnical engineering assessment may be required to select the appropriate foundation repair or rebuild;

Residential Red – land was severely damaged beyond economical repair.

Figure 1.3: 2002 Liquefaction Hazard Map



Note: This map was digitalized from the Christchurch Liquefaction Study - Stage II ECan Report NO. U02/2002, and geo-referenced and converted into shapefile in ArcGIS by the author.

Three liquefaction hazard classes from the 2002 study:

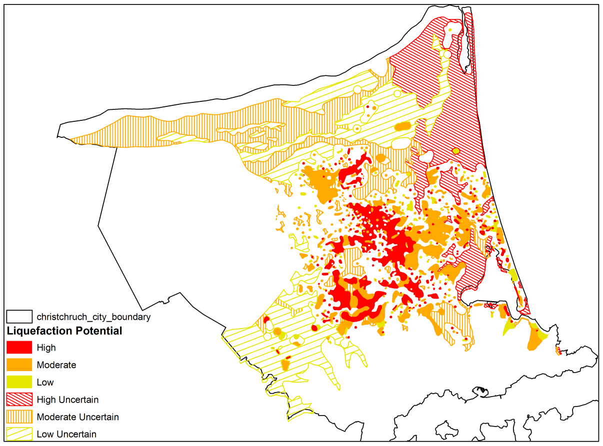
High - high liquefaction potential;

Moderate - moderate liquefaction potential;

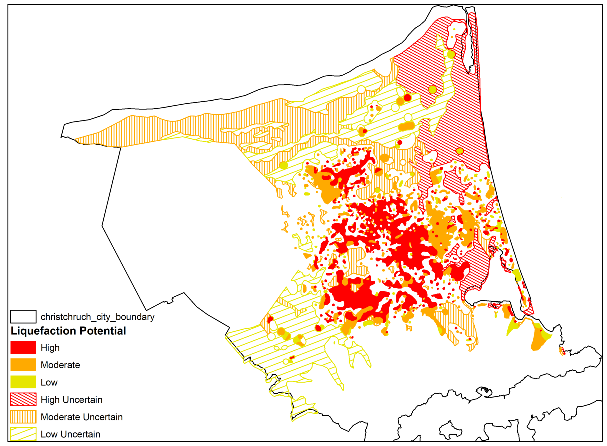
Low - low liquefaction potential.

Figure 1.4: 2005 Liquefaction Hazard Map

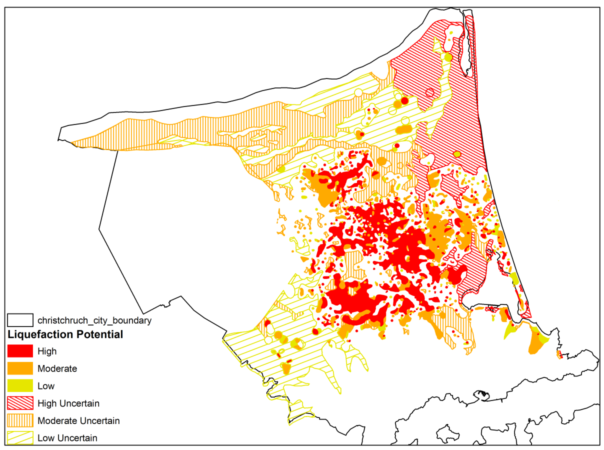
(a) Summer Groundwater Level



(b) Winter Groundwater Level



(c) Joint



Note: This map was retrieved from the Christchurch Liquefaction Study - Stage IV (Addendum Report) ECan Report NO. U04/25/2. The shapefiles of summer and winter maps were provided by ECan. The summer and winter maps were combined to produce the joint map in ArcGIS by the author.

Six liquefaction hazard classes from the 2005 study:

High - high liquefaction potential;

Moderate - moderate liquefaction potential;

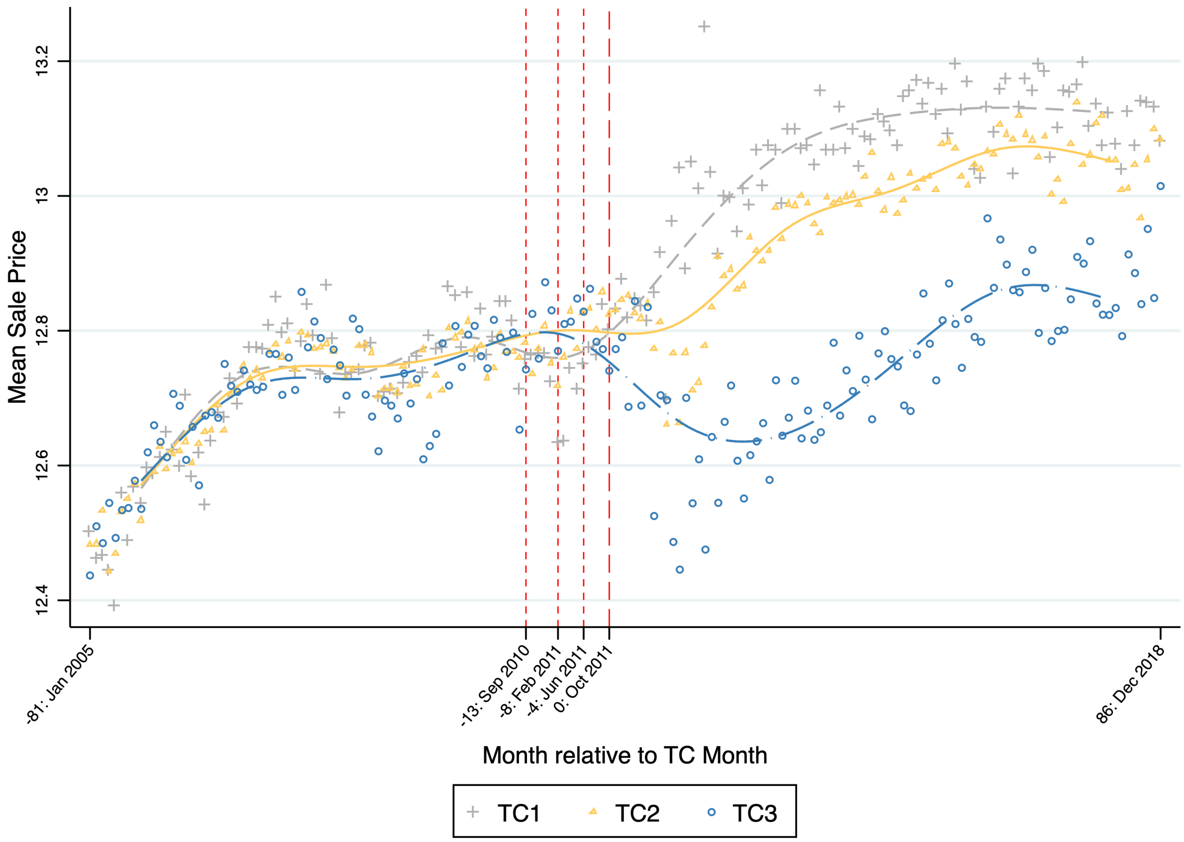
Low - low liquefaction potential;

High uncertain - insufficient information available, but may have high liquefaction potential;

Moderate uncertain - insufficient information available, but may have moderate liquefaction potential;

Low uncertain - insufficient information available, but may have low liquefaction potential.

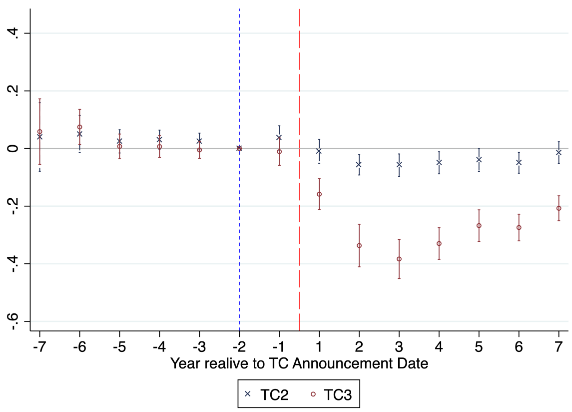
Figure 1.5: Mean of Log of Selling Price Relative to the TC Announcement Month



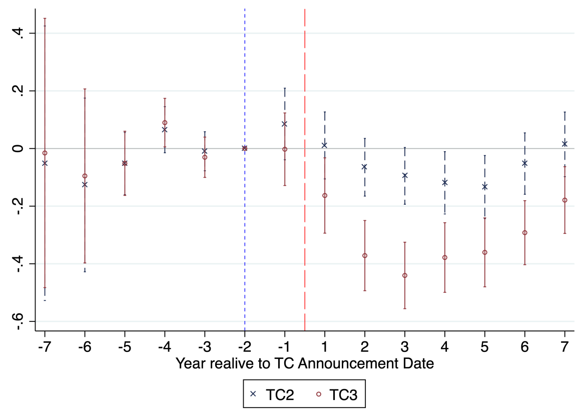
Note: This figure presents the mean of log of selling price relative to the TC announcement month by TCs from 2005 to 2018. The three short dashed red lines indicate the months of the three major quakes, and the long dashed red line indicates the month of the TC announcement.

Figure 1.6: Dynamic TC Effects

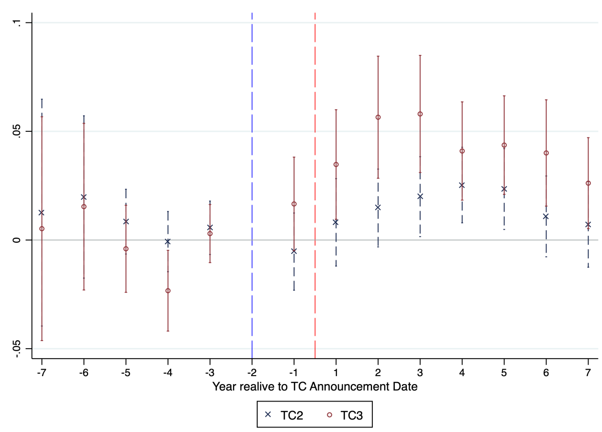
(a) TC Effects: w/o Distance to Red Zone



(b) TC Effects: w/ Distance to Red Zone

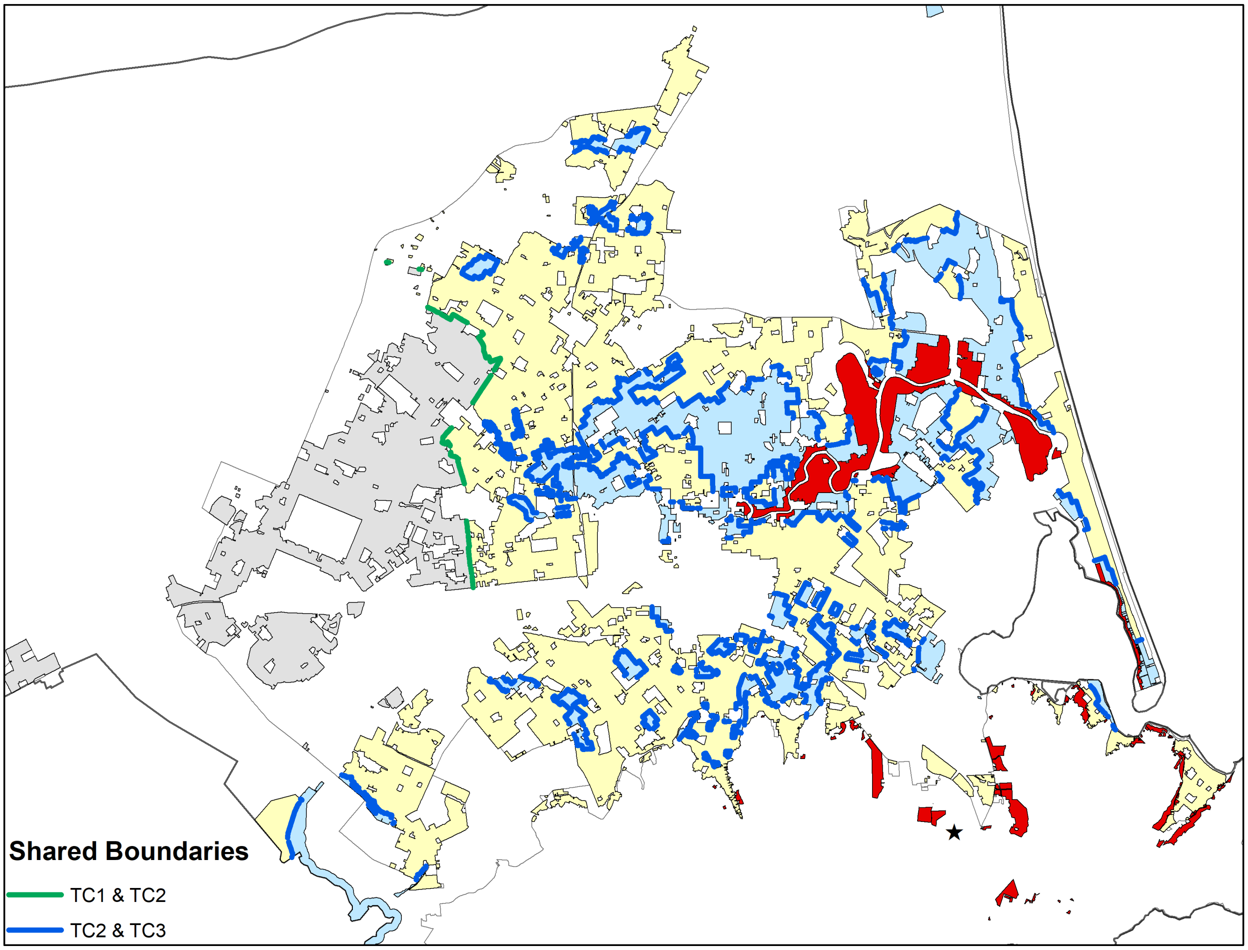


(c) Distance to Red Zone



Note: The blue dashed vertical line indicates the base time (Oct 28, 2009 – Oct 27, 2010): -2, two years before the TC zoning. Panel (a) presents the estimates from the model without controlling for the distance to the residential red zones. Panels (b) and (c) present the estimates from the model with distance to residential red zone controls.

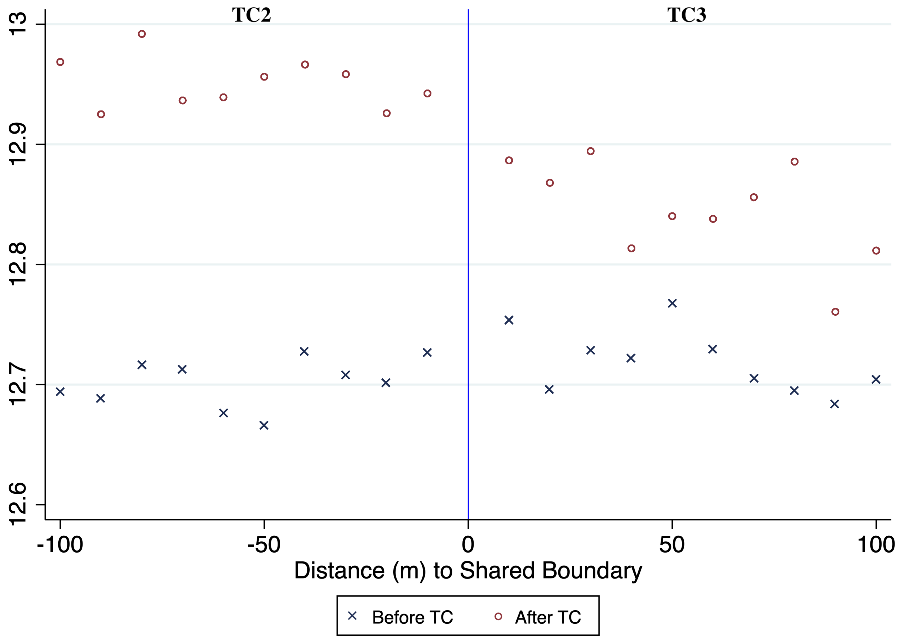
Figure 1.7: Shared Boundaries



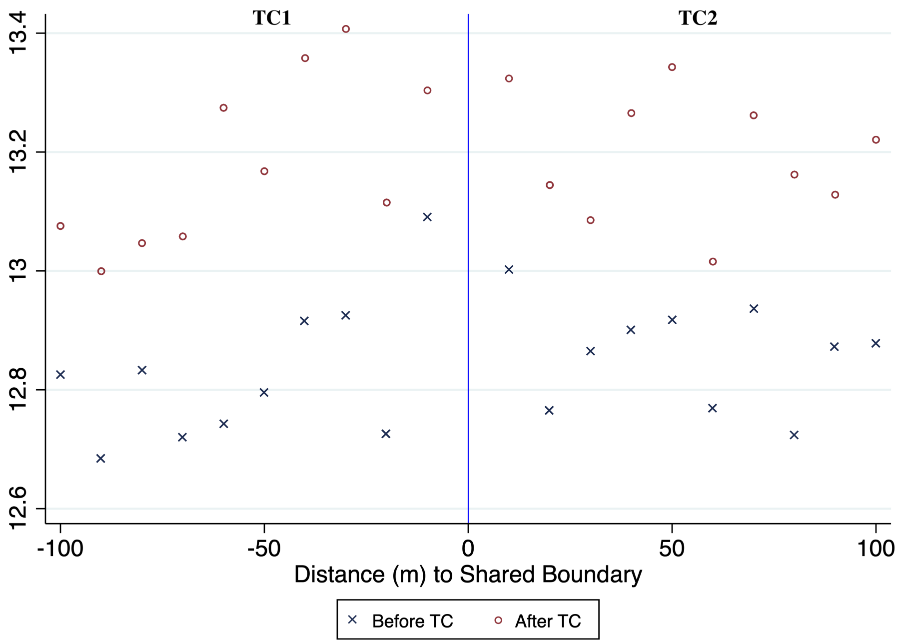
Note: This map presents the shared boundaries between TCs.

Figure 1.8: Mean of Log of Selling Price on the Shared Boundaries

(a) TC2 vs TC3



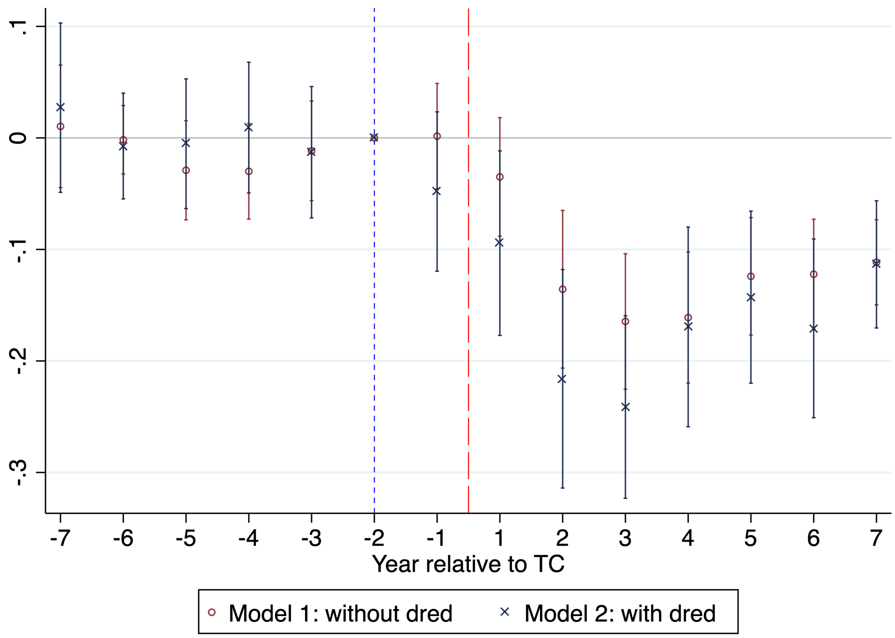
(b) TC1 vs TC2



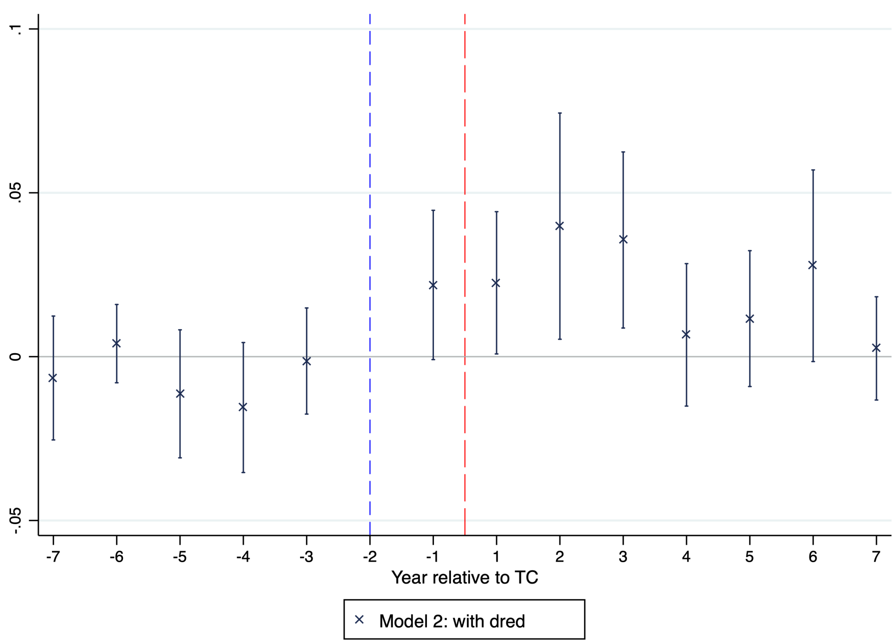
Note: These figures present the mean of selling price by distance to the shared boundaries of TCs.

Figure 1.9: Dynamic effects on the Shared Boundaries Between TC2 and TC3

(a) Dynamic Effects: TC3



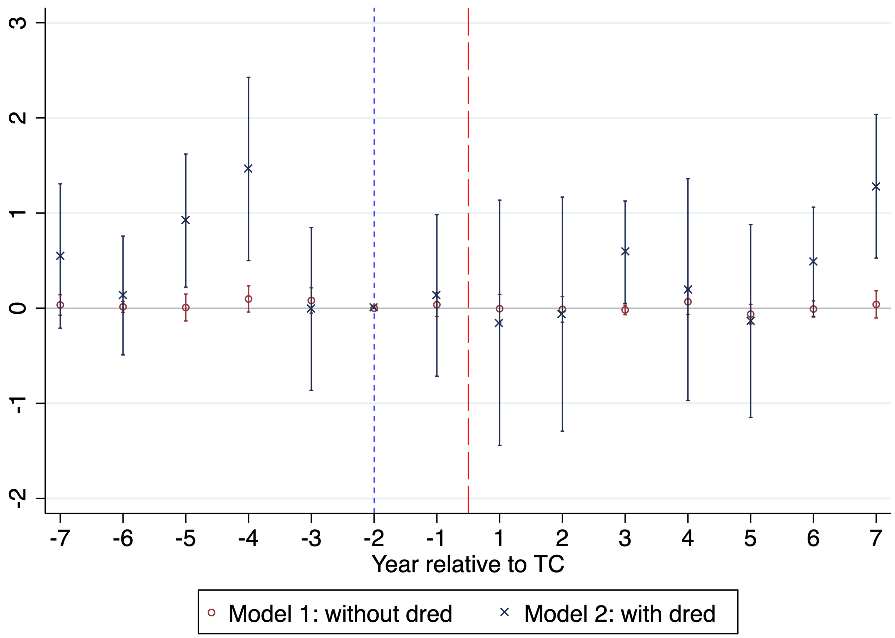
(b) Dynamic Effects: TC3 ×Distance to Red Zone



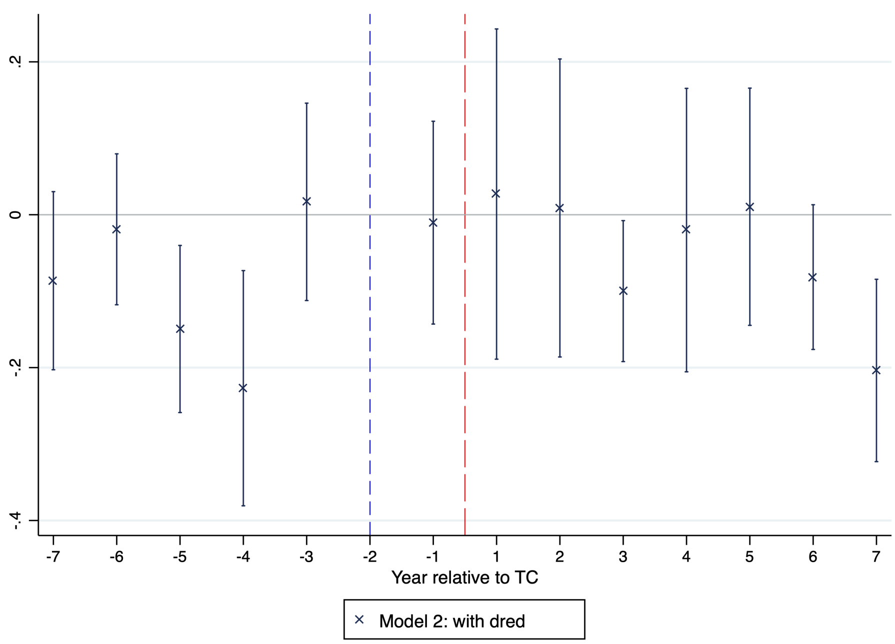
Note: These figures present the dynamic effects on the shared boundaries of TC2 and TC3. The reference TC is TC2. The blue dashed vertical line indicates the base time (Oct 28, 2009 – Oct 27, 2010): -2, two years before the TC zoning.

Figure 1.10: Dynamic effects on the Shared Boundaries Between TC1 and TC2

(a) Dynamic Effects: TC2



(b) Dynamic Effects: TC2 ×Distance to Red Zone



Note: These figures present the dynamic effects on the shared boundaries of TC1 and TC2. The reference TC is TC1. The blue dashed vertical line indicates the base time (Oct 28, 2009 – Oct 27, 2010): -2, two years before the TC zoning.

Table 1.1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Selling Price (NZ$)	331,438.11	168,410.37	34,300.00	1,300,000.00
Floor Area (m^2)	154.37	56.29	70.00	358.00
Land Area (m^2)	667.68	172.21	216.00	2001.00
Built in 1910s	0.03	0.17	0.00	1.00
Built in 1920s	0.10	0.30	0.00	1.00
Built in 1930s	0.04	0.19	0.00	1.00
Built in 1940s	0.06	0.23	0.00	1.00
Built in 1950s	0.13	0.34	0.00	1.00
Built in 1960s	0.16	0.37	0.00	1.00
Built in 1970s	0.10	0.30	0.00	1.00
Built in 1980s	0.06	0.24	0.00	1.00
Built in 1990s	0.08	0.27	0.00	1.00
Built in 2000s	0.20	0.40	0.00	1.00
Built in 2010s	0.04	0.19	0.00	1.00
Superior design and first class quality	0.07	0.25	0.00	1.00
Average design and quality	0.89	0.31	0.00	1.00
Below Average design and quality	0.04	0.20	0.00	1.00
No appreciable view	0.97	0.16	0.00	1.00
Water View	0.01	0.09	0.00	1.00
Other than water View	0.02	0.14	0.00	1.00
1 or 2 Bedrooms	0.07	0.25	0.00	1.00
3 Bedrooms	0.57	0.50	0.00	1.00
4 Bedrooms	0.32	0.47	0.00	1.00
5 Bedrooms	0.05	0.22	0.00	1.00
1 Bathrooms	0.67	0.47	0.00	1.00
2 Bathrooms	0.30	0.46	0.00	1.00
3 Bathrooms	0.03	0.18	0.00	1.00
1 Carparks	0.26	0.44	0.00	1.00
2 Carparks	0.69	0.46	0.00	1.00
3 Carparks	0.05	0.21	0.00	1.00
4 Carparks	0.01	0.09	0.00	1.00
Wall: Brick	0.34	0.47	0.00	1.00
Wall: Concrete	0.23	0.42	0.00	1.00
Wall: Roughcast	0.13	0.34	0.00	1.00
Wall: Weatherboard	0.22	0.41	0.00	1.00
Wall: Mixed Material	0.05	0.22	0.00	1.00
Wall: Other	0.03	0.18	0.00	1.00
Roof: Steel/G-Iron	0.53	0.50	0.00	1.00
Roof: Tile Profile	0.44	0.50	0.00	1.00
Roof: Other	0.02	0.15	0.00	1.00
Dist. from CBD (km)	4.60	2.28	0.00	14.49
Dist. from Christchurch Coast (km)	7.08	4.01	0.02	17.10
Dist. from the nearest Public Hospital (km)	3.84	1.92	0.17	11.95
Dist. from the nearest Private Hospital (km)	5.05	2.42	0.09	13.56
Dist. from the nearest Regional Park (km)	2.48	1.87	0.00	7.85
Dist. from the nearest Botanical Park (km)	1.80	1.50	0.00	8.04
Dist. from the nearest Community Park (km)	0.21	0.16	0.00	1.97
Dist. from the nearest Sports Park (km)	0.40	0.28	0.00	3.65
Dist. from the nearest Water Body (km)	1.40	0.77	0.01	3.63
Dist. from the nearest Residential Red Zone (km)	3.83	2.98	0.00	14.49
Elevation (m)	11.44	8.07	1.00	43.00
Technical Category 1 (gray)	0.19	0.35	0.00	1.00
Technical Category 2 (yellow)	0.61	0.49	0.00	1.00
Technical Category 3 (blue)	0.21	0.40	0.00	1.00
Number of Observations		91,748		

Note: This table presents summary statistics for the City of Christchurch from year 2000 to 2018.

Table 1.2: Long-Run Effects of Technical Categories on Log of Property Price

	Baseline DID				CPAR-SemiP			
	(1)		(2)		(3)		(4)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
TC2 ×post1	0.001	(0.025)	0.002	(0.024)	0.011	(0.017)	0.012	(0.017)
TC3 ×post1	0.001	(0.027)	0.002	(0.027)	0.011	(0.022)	0.010	(0.022)
TC2 ×post2	0.015	(0.036)	0.016	(0.035)	0.012	(0.027)	0.015	(0.027)
TC3 ×post2	−0.019	(0.042)	−0.004	(0.041)	0.001	(0.042)	0.020	(0.042)
TC2 ×post3	−0.010	(0.031)	−0.012	(0.031)	−0.008	(0.026)	−0.010	(0.026)
TC3 ×post3	−0.081**	(0.040)	−0.088**	(0.039)	−0.106**	(0.044)	−0.115***	(0.044)
TC2 ×post4	−0.074***	(0.028)	−0.039	(0.060)	−0.082***	(0.016)	−0.091***	(0.026)
TC3 ×post4	−0.218***	(0.039)	−0.208***	(0.067)	−0.220***	(0.025)	−0.255***	(0.032)
dred (km)			−0.005	(0.045)			−0.062***	(0.011)
dred ×post4			0.012*	(0.007)			0.007***	(0.002)
TC2 × dred			−0.015	(0.040)			0.008	(0.010)
TC3 × dred			−0.021	(0.040)			0.000	(0.010)
TC2 × dred ×post4			0.008	(0.009)			0.014***	(0.003)
TC3 × dred ×post4			0.040***	(0.010)			0.047***	(0.004)
AdjustedR^2	0.612		0.616					
AIC	2272.373		1571.121					
Number of Observations	62,149							
Baseline Mean $Log(P)$	12.680							

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents the long-run average effects of TC for log of property price for the City of Christchurch for the period 2005–2018. The reference group is the TC1. Columns (1) and (2): standard errors are clustered at area unit levels. Baseline DID models are estimated with structural and amenity controls, year, seasonal and area unit fixed effects. Columns (3) and (4): geographical coordinates are used instead of area unit fixed effects. In the conditionally parametric (CPAR) and semiparametric (SeimP) models, coefficient estimates of structural and amenity controls are allowed to vary smoothly over space, while coefficient estimates of variables listed in this table as well as coefficient estimates of year and seasonal fixed effects are modeled to be constant over space. Both CPAR-SemiP models are estimated at the window size of 30% and using a tri-cubic kernel function $\frac{70}{81}(1-(|z|)^3)^3 * I(|z|<1)$.

Table 1.3: Dynamic Effects of the TCs

	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
TC2 × -7	0.040	(0.060)	−0.051	(0.240)
TC2 × -6	0.050	(0.032)	−0.126	(0.152)
TC2 × -5	0.025	(0.020)	−0.052	(0.054)
TC2 × -4	0.030*	(0.017)	0.065	(0.040)
TC2 × -3	0.024*	(0.015)	−0.010	(0.034)
TC2 × -1	0.037*	(0.021)	0.085	(0.063)
TC2 × 1	−0.010	(0.021)	0.011	(0.059)
TC2 × 2	−0.057***	(0.018)	−0.065	(0.050)
TC2 × 3	−0.058***	(0.020)	−0.095*	(0.050)
TC2 × 4	−0.050**	(0.019)	−0.119**	(0.055)
TC2 × 5	−0.040**	(0.020)	−0.134**	(0.055)
TC2 × 6	−0.050***	(0.018)	−0.052	(0.054)
TC2 × 7	−0.014	(0.019)	0.015	(0.057)
TC3 × -7	0.059	(0.057)	−0.016	(0.236)
TC3 × -6	0.075**	(0.031)	−0.095	(0.152)
TC3 × -5	0.007	(0.022)	−0.051	(0.056)
TC3 × -4	0.007	(0.019)	0.090**	(0.043)
TC3 × -3	−0.005	(0.015)	−0.030	(0.035)
TC3 × -1	−0.011	(0.024)	−0.002	(0.064)
TC3 × 1	−0.159***	(0.027)	−0.163**	(0.066)
TC3 × 2	−0.337***	(0.037)	−0.372***	(0.061)
TC3 × 3	−0.353***	(0.034)	−0.441***	(0.058)
TC3 × 4	−0.330***	(0.028)	−0.378***	(0.061)
TC3 × 5	−0.268***	(0.028)	−0.360***	(0.060)
TC3 × 6	−0.274***	(0.023)	−0.292***	(0.056)
TC3 × 7	−0.207***	(0.022)	−0.179***	(0.058)
TC2 × dred × -7			0.013	(0.026)
TC2 × dred × -6			0.020	(0.019)
TC2 × dred × -5			0.008	(0.008)
TC2 × dred × -4			−0.001	(0.007)
TC2 × dred × -3			0.006	(0.006)
TC2 × dred × -1			−0.005	(0.009)
TC2 × dred × 1			0.008	(0.010)
TC2 × dred × 2			0.015	(0.009)
TC2 × dred × 3			0.020**	(0.009)
TC2 × dred × 4			0.025***	(0.009)
TC2 × dred × 5			0.023**	(0.009)
TC2 × dred × 6			0.011	(0.009)
TC2 × dred × 7			0.007	(0.010)
TC3 × dred × -7			0.005	(0.026)
TC3 × dred × -6			0.015	(0.019)
TC3 × dred × -5			−0.004	(0.010)
TC3 × dred × -4			−0.023**	(0.009)
TC3 × dred × -3			0.003	(0.007)
TC3 × dred × -1			0.017	(0.011)
TC3 × dred × 1			0.035***	(0.013)
TC3 × dred × 2			0.056***	(0.014)
TC3 × dred × 3			0.058***	(0.014)
TC3 × dred × 4			0.041***	(0.011)
TC3 × dred × 5			0.044***	(0.011)
TC3 × dred × 6			0.040***	(0.012)
TC3 × dred × 7			0.026**	(0.011)
Adjusted R^2	0.613		0.618	
AIC	2071.156		1253.496	
Number of Observations	62,149			
Baseline Mean $log(P)$	12.78			

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents the dynamic effects of TC for log of property price for the City of Christchurch for the period 2005–2018. The reference group is TC1 and the reference transaction time is 2 years before TC announcement (Oct 28, 2009 – Oct 27, 2010). Both models include amenity controls, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Table 1.4: Placebo Tests – Falsified Technical Categories and Falsified Event Dates

Panel A: Placebo Test 1 – Falsified Technical Categories				
	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
Moderate × post1	0.001	(0.024)	−0.004	(0.026)
High × post1	0.038	(0.032)	0.034	(0.033)
Moderate × post2	0.037	(0.054)	0.041	(0.055)
High × post2	0.059	(0.048)	0.054	(0.049)
Moderate × post3	−0.048	(0.072)	−0.049	(0.071)
High × post3	−0.054	(0.071)	−0.050	(0.071)
Moderate × post4	−0.043	(0.043)	0.057	(0.056)
High × post4	−0.080	(0.051)	0.052	(0.055)
dred (km)			−0.036	(0.023)
dred × post4			0.034***	(0.011)
Moderate × dred			0.002	(0.009)
High × dred			−0.001	(0.009)
Moderate × dred × post4			−0.012	(0.011)
High × dred × post4			−0.019	(0.012)
Adjusted R^2	0.618		0.622	
AIC	70.318		-175.468	
Sample Period	2005 - 2018			
Number of Observations	24,148			
Baseline Mean $log(P)$	12.66			
Panel B: Placebo Test 2 – Falsified Zoning Date				
TC2	0.118***	(0.036)	0.146***	(0.044)
TC3	0.158***	(0.040)	0.198***	(0.050)
post	−0.013	(0.026)	0.013	(0.026)
TC2 × post	−0.015	(0.029)	−0.000	(0.032)
TC3 × post	−0.035	(0.027)	−0.029	(0.032)
Sample Period	2005 - Aug 2010		2005 - 2007	
Falsified Date	Oct 1, 2007		Jun 1, 2006	
Adjusted R^2	0.570		0.539	
Number of Observations	29,927		18,836	
Baseline Mean $log(P)$	12.63		12.55	

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents the estimates of placebo tests. The reference groups are "Low" and TC1 in panels A and B, respectively. All models include amenity controls, year, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Table 1.5: DID: 100 Meter from the Shared Boundaries

Panel A: TC2 vs TC3				
	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
TC3 × post1	0.046	(0.030)	0.046	(0.029)
TC3 × post2	−0.028	(0.049)	−0.007	(0.048)
TC3 × post3	−0.040	(0.049)	−0.059	(0.048)
TC3 × post4	−0.097***	(0.030)	−0.145***	(0.033)
dred (km)			−0.041	(0.027)
dred × post4			0.016***	(0.005)
TC3 × dred			−0.009***	(0.003)
TC3 × dred × post4			0.023***	(0.005)
Adjusted R^2	0.667		0.671	
AIC	70.728		-89.019	
Number of Observations	12,190			
Baseline Mean $log(P)$	12.69			
Panel B: TC1 vs TC2				
TC2 × post1	−0.051	(0.075)	−0.043	(0.072)
TC2 × post2	0.112	(0.083)	0.103	(0.080)
TC2 × post3	−0.005	(0.063)	−0.009	(0.063)
TC2 × post4	−0.088	(0.049)	−0.060	(0.209)
dred (km)			−5.223	(4.677)
dred × post4			−0.030	(0.031)
TC2 × dred			−0.027	(0.030)
TC2 × dred × post4			−0.004	(0.030)
Adjusted R^2	0.808		0.808	
AIC	-848.224		-853.557	
Number of Observations	701			
Baseline Mean $log(P)$	12.79			

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents the DID estimates on the shared boundaries. It covers years 2005 to 2018. The reference TC is TC2 and TC1 in panels A and B, respectively. All models include amenity controls, year, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Table 1.6: Alternative Earthquake Impact Period

	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
TC2 × e1	0.001	(0.025)	0.003	(0.025)
TC3 × e1	0.002	(0.027)	0.002	(0.027)
TC2 × e2	0.013	(0.049)	0.016	(0.047)
TC3 × e2	−0.019	(0.053)	−0.004	(0.051)
TC2 × e3	0.007	(0.035)	0.008	(0.034)
TC3 × e3	−0.097**	(0.040)	−0.089**	(0.040)
TC2 × e4	−0.069***	(0.019)	−0.034	(0.063)
TC3 × e4	−0.316***	(0.025)	−0.299***	(0.064)
dred (km)			−0.005	(0.045)
dred × e4			0.012*	(0.007)
TC2 × dred			−0.015	(0.040)
TC3 × dred			−0.021	(0.040)
TC2 × dred × e4			0.008	(0.009)
TC3 × dred × e4			0.040***	(0.010)
Adjusted R^2	0.612		0.616	
AIC	2,273.210		1,572.857	
Number of Observations	62,149			
Baseline Mean $log(P)$	12.68			

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Note: This table presents the regression results from using alternative earthquake impact periods. Earthquake effects are assumed to be transient. It covers years 2005 to 2018. The reference TC is TC1. All models include amenity controls, year, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Chapter 2

Is There a Slope Discount?

2.1 Introduction

Land is one of the more critical inputs in any production function (Chakravorty, 2013). Its use is possibly the most essential feature that determines urban structure and urban growth and its value shapes the dynamics of the real estate markets. Bostic *et al.* (2007) introduce the land leverage hypothesis that states that houses with greater land leverage - land accounts for a large fraction of house value - experience a higher price appreciation in a market absent any increase in construction cost. Davis *et al.* (2017) find much more volatile land prices than house price patterns in the Washington DC metro area from 2000 to 2013. In addition, they find that variations in land leverage during boom periods notably predict variations in house prices in the bust periods.

Land values are also important from other aspects. From an individual household's perspective, land value represents a large portion of an individual household's wealth. From the local government's perspective, land value affects the land-use regulations (and vice versa), hence urban structure, urban growth, and property taxes. From the national perceptive, land value is an important part of the National Balance Sheet. Although it has such a critical role in the economy, data on land values are often difficult to access.

Given the dearth of information on land values, land price is typically measured using one of the following decomposition methods in the current literature: the vacant land method, the construction cost method and the hedonic regression methods. In the housing price literature, it is long recognized that housing characteristics should be controlled for to have a constant quality in the housing price index. Similarly, in the price decomposition literature, it is well established that physical attributes of a house, especially age, cannot be ignored if one is to obtain a constant quality price index. However, the literature on the importance of land qualities is still quite scarce. Just like other price indices, the ideal land price index should represent changes in prices of land that are comparable in quality over time.

In the urban development literature, the importance of geographic features such as proximity to a waterbody, mountains or wetlands on urban development and housing supply has generated a growing literature that has focused on measuring the role of amenities. For instance, Burchfield *et al.* (2006) relate terrain ruggedness and access to underground water to the density and compactness of new real estate development. Saiz (2010) shows that residential development is considerably constrained by the presence of steep-sloped terrain and find that most areas with inelastic housing supply are severely land-constrained by their geography.

In this paper, an attempt will be made to fill the gap in the decomposition literature by modeling land qualities measured by land slope, a factor that possibly discount land price, to estimate quality adjusted land price indices. Having constant quality land price indices, similar to having constant quality structure price indices, requires land qualities, such as land area and location, to be constant over time. Of equal importance is the need to take account of the physical attributes of the land itself especially land slope, for they impose constraints on the development and use of land. Sloping land adds complexity to construction such as extra drainage and extra work in stepping the foundations, hence increases the construction cost of a house. Moreover, the degree of slope of a piece of land may limit its use and development, hence discounts the value of the land. On the other hand, sloping land may afford better views, hence increasing property values. However, this potential positive attribute is not addressed in this paper due to lack of data. This paper adopts and extends the builder's model developed by Diewert *et al.* (2011) by incorporating terrain slope to the generalized builder's model. Land parcel slopes are prepared in three steps. First, terrain slopes are calculated from the 2013 1-meter Digital Elevation Data (DEM) for Auckland. Mean terrain slopes are then formed for each land parcel extracted from the map of New Zealand Primary Land Parcels. The Address Information Management System (AIMS) from Land Information New Zealand (LINZ) is used next to link land parcels to addresses in the monthly sales data. In the present paper within the confined study area in Auckland with hilly features, the results reveal a slope discount on the price of land per square meter, controlling for land size (m^2), land location (in terms of school attendance zone), floor area (m^2), decade age of the house, and number of rooms. The constant quality land price indices from the generalized builder's model decreases moderately after controlling for terrain slope, whereas the imputed Fisher chained house price index remained almost unchanged. On the whole, land slope does appear to be an important hedonic characteristic associated with land and hence house values. Yet, when land slope compositions do not change over time, having land slope as an additional land characteristic generates minimum effects on the estimated land price indices.

In the rest of the paper, both the standard and generalized builder's models are described. Thereafter, the generalized builder's model is extended to incorporate the terrain slopes. The sales data are reviewed, and land slope is constructed in section 2.3. Section 2.4 presents the exogenous information on the price of the structure prior to the estimation and discussion of the quality-adjusted land, structural and Fisher chained house price indices. A summary section concludes the paper.

2.2 Model

There are four primary types of methods for computing residential property price indices: stratification, repeat-sales, appraisal-based methods and hedonic regression.[1] Most recently, Lopez and Hewings (2018) introduce a method that is a generalization of the repeat sales (Case-Shiller) but more flexible; the idea was first suggested by McMillen (2012). The hedonic regression method is typically the best approach for constructing a constant quality residential property price index. A typical hedonic estimator expresses housing prices or log of housing prices as a linear function of structure and location attributes. The commonly used hedonic approaches for computing price indices include hedonic imputation method and hedonic price method with time dummy variables.

For the hedonic imputation method, a hedonic regression is initially estimated for each time period separately. For example, consider there are N^0 and N^1 houses with K characteristics $z_i^0(z_{i1}^0, z_{i2}^0, \cdots, z_{ik}^0)$ and $z_i^1(z_{i1}^1, z_{i2}^1, \cdots, z_{ik}^1)$ sold in period 0 and period 1, respectively.

[1] See Bailey *et al.* (1963); Bourassa *et al.* (2006); Clapp and Giaccotto (1992); De Vries *et al.* (2009); Wallace and Meese (1997); Wood *et al.* (2005); Shiller (1991).

The following hedonic functions are estimated first:

$$\hat{p}_i^0 = h^0(z_i^0) = \hat{\alpha}^0 + \sum_{k=1}^{K} \hat{\beta}_k^0 \times z_{ik}^0$$

$$\hat{p}_i^1 = h^1(z_i^1) = \hat{\alpha}^1 + \sum_{k=1}^{K} \hat{\beta}_k^1 \times z_{ik}^1$$

where $\hat{p}_i^t$ is the predicted selling price of house i sold in period t. Next, the change in the quality-controlled house price between two periods is constructed as the price difference between the observed house price in one period and the imputed price if the characteristics from this period were evaluated at the estimated attributes prices in the earlier period. The imputed period 1 price of period 0 housing characteristics is denoted as $h^1(z_i^0)$, and, similarly, the imputed period 0 price of period 1 housing characteristics is denoted as $h^0(z_i^1)$. Holding housing characteristics constant in period 0 and period 1 separately, we can construct, for example, the following quality-adjusted imputed house price indices:

$$\text{Hedonic Laspeyres Price Index} = \frac{\sum_{i=1}^{N^0} h^1(z_i^0)}{\sum_{i=1}^{N^0} h^0(z_i^0)}$$

$$\text{Hedonic Paasche Price Index} = \frac{\sum_{i=1}^{N^1} h^1(z_i^1)}{\sum_{i=1}^{N^1} h^0(z_i^1)}$$

Other important imputed price indices include Fisher, Geometric-Paasche, Geometric-Laspeyres and Törnqvist price indices (Hill and Melser, 2008).

The hedonic price method with time dummy variables, as the name suggests, expresses house prices from the cross-sectional data that are available over time as a linear combination of structure and location attributes (i.e., quality controlled) and a set of time dummies in a single equation. Estimated co-effects of the time dummies are the price indices and represent the price differences between time t and the base year).

$$ln(\hat{p}_{it}) = \hat{\alpha} + \sum_{t=2}^{T} \hat{\delta}_t D_{it} + \sum_{k=1}^{K} \hat{\beta}_k z_{it,k},$$

where D_{it} is a set of dummy variables that takes on the value of 1 if the house i is sold at time t and 0 otherwise. $\hat{\delta}_t$ is interpreted as the quality-adjusted price difference between time t and the base time. A quality-adjusted price index can also be obtained.

With the hedonic approaches, a notable problem is that there is often a high correlation between the explanatory variables making the estimated coefficients unstable. As discussed in OECD *et al.* (2013), multicollinearity is less of a concern if the purpose is to construct the overall constant quality house price index. However, when the parameters of interest are the coefficients of the physical attributes (e.g., number of bedrooms) and particularity when the interest is to decompose the overall price index into the land price index and the structure price index, multicollinearity can be a real problem.[2]

2.2.1 Standard Builder's Model

The builder's model is first discussed by Diewert (2008) and introduced by Diewert *et al.* (2011) to decompose residential price indices into two sub-price indices: a quality adjusted price index for the structure and a price index for the land on which the property is built. The derivation originates from a cost of production approach; from a builder's perspective, the selling price of any property after completion is its expected cost. The total expected cost of a property is denoted as the sum of the cost of structure and the cost of the land on which it is built. The cost of the structure is measured as the floor area (e.g., square meter

[2] See also Schwann (1998) and Diewert *et al.* (2011, 2015); Diewert and Shimizu (2016) for the discussion of multicollinearity.

m^2) of the property multiplied by the unit cost of construction (e.g., construction cost per square meter). The cost of land is measured as land area (e.g., square meter m^2) multiplied by the unit cost of land (e.g., cost per square meter). Mathematically, the basic builder's model has the following additive and non-linear form[3]:

$$p_{it} = p_t^L L_{it} + p_t^S S_{it} + \varepsilon_{it}, \tag{2.1}$$

where p_{it} is the selling price of property i at time t; p_t^L and p_t^S are prices of land and structure per square meter at time t, respectively; L_{it} is the area of land property i is built on at time t; S_{it} is the floor area property i at time t; error terms ε_{it} are assumed to be heteroskedastic, not serially correlated and mean independent of covariates.

In essence, the hedonic regression defined in equation (2.1) only works for newly built properties. To acknowledge the fact that properties sold at time t include not only newly built properties but also existing older properties, and older properties are usually worth less than newer properties because of structure depreciation over time, equation (2.1) is commonly modified by incorporating the age of a property into the baseline builder's model:

$$p_{it} = p_t^L L_{it} + p_t^S (1 - \delta A_{it}) S_{it} + \varepsilon_{it}, \tag{2.2}$$

where A_{it} is the age of property i at time t; δ is the net straight-line deprecation rate as the structures of properties age.[4] Common units of measurement for A_{it} include year and decade. Hence, δ can be either the annual net depreciation rate or decade net depreciation rate.[5] If properties are maintained well or renovated over time, the deterioration of aged

[3] The assumption that land and structure values are additive is suggested in most of the literature including but not limited to Bostic *et al.* (2007); Diewert (2008); Diewert *et al.* (2011, 2015); Diewert and Shimizu (2016); De Haan and Diewert (2013) and Francke and van de Minne (2017).

[4] One can also assume that deprecation rates change over time: $p_{it} = p_t^L L_{it} + p_t^S (1 - \delta_t A_{it}) S_{it} + \varepsilon_{it}$.

[5] Reasonable annual net depreciation rates are in the 0.5 - 2% range.

properties can be slowed down (and, in some cases, older properties may command a premium). Knight and Sirmans (1996) find that houses with maintenance levels that are lower than average deprecate 0.9% faster per year. Harding *et al.* (2007) find that well maintained houses deprecate 0.5% less per year than the average. Moreover, older structures can produce functional obstacles as suggested in Rubin (1993) and negatively affect property values. Nevertheless, as structures age, some aspects of structures, such as design of a certain construction period, may induce a positive effect on property values. This is recognized as the vintage effect (Coulson and Lahr, 2005), which can even offset the negative effects of age.[6] Coulson and McMillen (2008) extend the method proposed by McKenzie (2006) to estimate the time, age and cohort (vintage) effects simultaneously. Their results show a U-shaped effect of age on housing prices. On the one hand, property prices decrease significantly in the first few years post construction while, on the other hand, very old houses have notable price premium. More recently, Francke and van de Minne (2017) estimate all three age effects on property structures and the time effect on land values. Since only age enters as the structure predictor in the builder's model, δ should be interpreted as the net effect of age on structure of a property. $(1-\delta A_{it})S_{it}$, then, can be interpreted as older structures measured in units of new or more recent structures. Therefore, without maintenance information, very old structures have been excluded from the model.[7]

The problem with the straight-line method of modeling depreciation is that the value of the structure can become negative if the age of the structure is large. Therefore, the geometric method is commonly used in national accounts as an alternative to the straight-

[6] For example, Meese and Wallace (1991) find that housing prices increase with age.
[7] Burnett-Isaacs *et al.* (2017) define old houses if aged more than 60 years.

line method to avoid this problem. The Builder's model with geometric depreciation has the following form:

$$p_{it} = p_t^L L_{it} + p_t^S (1-\delta)^{A_{it}} S_{it} + \varepsilon_{it}, \tag{2.3}$$

where δ is the net geometric deprecation rate as the structures of properties age. With geometric depreciation, structures deteriorate at a constant rate over time, whereas structures deteriorate by constant amounts with straight-line depreciation. In practice, empirical studies, such as Chinloy (1977) and Malpezzi *et al.* (1987), suggest that it is more appropriate to use the geometric method for residential properties.

2.2.2 Generalization of Standard Builder's Model

Diewert (2008) suggests that the basic hedonic decomposition can be generalized to incorporate more physical attributes used in standard hedonic model in the following way. Suppose $Z_1, \ldots, Z_M$ are M determinant attributes for quality of land and $X_1, \ldots, X_H$ are H determinant attributes for quality of structure, the generalized builder's model with geometric depreciation is:

$$p_{it} = p_t^L (1 + \sum_{m=1}^{M} \lambda_m Z_{it,m}) L_{it} + p_t^S (1-\delta)^{A_{it}} (1 + \sum_{h=1}^{H} \eta_h X_{it,h}) S_{it} + \varepsilon_{it}, \tag{2.4}$$

where p_t^L is the quality adjusted price for land at time t, and p_t^S is the quality adjusted price for structures at time t. In the literature, characteristics used to control for the quality of land are the locations of the land. Location-related attributes typically include distance to the city business center, zones (e.g. zip code or school zone), and street patterns of the land on which a property is built, such as at the intersection of two streets or at a cul-de-sac.[8]

[8] Recent work by Pan *et al.* (2018) suggests that distance from the CBD is just one of many attributes

Characteristics that are controlled for the quality of structure consist of physical attributes such as number of bathrooms and bedrooms.

For this paper, school zones will be incorporated into the model as one of the land characteristics and the numbers of rooms (sum of bedroom and bathroom) will be used as an additional structural attribute in the generalized model:

$$p_{it} = p_t^L(1+\sum_{z=1}^{Z}\lambda_z Zone_{it,z})L_{it} + p_t^S(1-\delta)^{A_{it}}(1+\sum_{r=1}^{R}\eta_r Room_{it,r})S_{it} + \varepsilon_{it}, \tag{2.5}$$

In this specification, both school zones and numbers of rooms enter as dummy variables; to avoid the dummy variable trap, one group from each is dropped.

2.2.3 Generalization of Builder's Model with Terrain Slope

The hedonic literature is rich in adjusting for structure qualities. The need for quality adjustment extends to land characteristics as well. Cheshire and Sheppard (1995) point out that as land itself is a composite good, the price of land is the price of pure land together with the prices of the bundle of neighborhood, environmental characteristics and local public goods embodied in land.

The theory of land use has its origin in the monocentric city model developed by Alonso *et al.* (1964); Mills (1967) and Muth (1969). The traditional monocentric city model treats land as a featureless flat plain so that locations only differ by distances to the Central Business District (CBD). Thus, the model predicts higher land prices and housing densities in places closer to CBD. Later urban economic models extend the monocentric city model to include environmental amenities such as open space (including but not limited to Anderson

valued by consumers and hence the land use changes in a metropolitan region nay reflect multiple dimensions of accessibility.

and West, 2006; Geoghegan, 2002 and Irwin, 2002) and allow for multi-centric structures (including but not limited to Anas and Kim, 1996; McDonald and McMillen, 1990 and Wieand, 1987) to explain a more complex spatial structure. The featureless flat plain assumption in urban economic models is relaxed in the more recent literature. For example, Keenan *et al.* (2018) develop a conceptual "climate gentrification" model and find that price appreciation is positively affected by the incremental increase in elevation in Miami-Dade County, Florida (the "elevation hypothesis"). Ye and Becker (2017) study seventeen US cities and find high-income households prefer to live at higher elevations. They also find the standard deviation of elevation and relative altitude positively affect density and housing value gradients.

Instead of elevation, the focus in this paper will be on terrain slope as a site-specific land attribute. If a site is flat,[9] the topography may not influence the location and layout of the building, but on a sloping site, the topography is likely to exert a significant influence on the house design. Sloping sites present a number of challenges and generally require a greater design input than flat sites. They generally require additional geodetic assessments of slope stability and earthworks before the actual house construction stage. Depending on the steepness of the slope, sloping sites usually have to be cut, filled and or retained to prepare a level plinth on which concrete slab foundations and floors can be laid out.[10] Building on a sloping site may also require additional drainage and sewers. Therefore, the overall construction costs on sloping sites are intrinsically higher than overall construction costs on flat sites essentially attributable to the amount of cut and fill and engineered retaining walls. These costs generally increase with the degree of slope.

[9] Flat areas are never strictly horizontal. Rather there are gentle slopes which are often hardly noticeable to the naked eye.

[10] Increasingly, new houses in New Zealand today are built on a concrete slab.

Consequently, in mountainous regions, land slopes would also generate a significant contribution to the formation of the quality-adjusted land prices. Driving around Auckland, it is apparent that land is not even. It is common to observe houses constructed along sloping driveways. If the sample of houses sold in time period t consists of more houses built on sloping sites compared to the sample of houses sold in previous period with similar structures but built on flat sites, changes in topographical characteristics should not be interpreted as changes in land prices over time. If slope has a negative effect on housing price, without controlling for slope would result in an underestimate of the land price index for time period t.

Acknowledging that the degree of slope places substantial limitations on the use of a piece of land and may add considerable costs to construction due to earthworks, land slope is modeled as a determinant of land price in addition to land size and the school zone that represents the location and public service associated with a site:

$$\begin{aligned} p_{it} = & p_t^L \left(1 + \sum_{z=1}^{Z} \lambda_z Zone_{it,z}\right)\left(1 + \sum_{s=1}^{S} \beta_s \, Slope\ Group_{it,s}\right) L_{it} \\ & + p_t^S (1-\delta)^{A_{it}} \left(1 + \sum_{r=1}^{R} \eta_r R_{it,r}\right) S_{it} + \varepsilon_{it} \end{aligned} \tag{2.6}$$

where p_t^L is the constant quality land price index (i.e., the "pure" price of land per square meter) and p_t^S is the constant quality structure price index as before.

If the ideal site for residential dwellings is that which furnishes the desired degree of space at the lowest costs, the difficulty of building on sloping land means that the price of a sloping site may be considerably cheaper than a flat site, hence decreasing property values. On the other hand, sloping land may provide better views, hence increasing property values. As a result of data limitations, neither information on the cost of slope-induced earthwork nor information on slope-induced appreciable view is obtained. Hence, the estimated coefficient of slope should be interpreted as the joint effect of the two opposing forces.

The following hypotheses summarize the possible effect of land slope on its hedonic price β_s.

> Hypothesis 1: If the difficulty to build on sloping sites dominates the possible view provided, a negative relationship between house price and land slope is expected.
>
> Hypothesis 2: If the possible view provided is more important than the difficulty to build on sloping sites, a positive relationship between house price and land slope is expected.
>
> Hypothesis 3: If either the difficulty to build on sloping sites is as important as the possible view provided or land slope is not an important house price determinant, a statistically non-significant relationship between house price and land slope is expected.

When it comes to construction of the quality-adjusted land price indices, the following cases summarize the possible change in land price indices once land slope is controlled for.

> Case 1: If slope has a negative (positive) effect on housing price, and if the sample of houses sold in time period t consists of more houses built on sloping sites compared to the sample of houses sold in the base period with similar structures but built on flat sites, controlling for slope would adjust the land price index for time period t upward (downward).

Case 2: If slope has a negative (positive) effect on housing price, but the composition of the houses sold, in terms of land slopes, does not differ in time period t and the base period, controlling for slope would not affect the land price index for time period t.

Case 3: If slope has no significant effect on housing price, regardless of the composition of the land slope over time, controlling for slope would not affect the land price index.

2.3 Data

2.3.1 Housing Sales Data

Monthly unit record 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 data encompasses school zones of Auckland Grammar School, Epsom Girl's Grammar School, Selwyn College, and One Tree Hill College and covers the period from January 2007 to January 2017. There are only 22 transactions in January 2017, of which 3 were in Double Grammar zone,[11] 8 in Selwyn College school zone and 11 in One Tree Hill College school zone. Therefore, they are coded as in year 2016 later to prepare for estimation.

Basic QV data includes selling prices, sales date, property address, floor area, land area, and various structural characteristics, school zone, Meshblock[12] number (New Zealand's counterpart to the US Census block), along with the property title information. The analysis is targeted to all types of houses but not apartments. In total, there are 17,966 observations.

[11] This zone includes Auckland Grammar School and Epsom Girl's Grammar School and hence is referred to as the Double Grammar zone.

[12] Meshblock is the smallest geographic unit for which statistical data is reported by Statistics New Zealand.

Dropping observations without sales prices information result in 17,796 transactions from 13,284 unique properties. By limiting the analysis to houses built on land for residential use, 114 observations were dropped.[13] 13 observations (12 unique properties) that are not for residential use were also dropped.[14] Further restricting the data to properties that are dwelling houses of a fully detached or semi-detached style situated on their own clearly defined piece of land reduces the sample size to 17,477. In addition, there are many observations with incomplete information on land and floor area. By focusing on observations with complete information on selling price, land area, floor area and building age reduces sample size to 10,052.

An examination of the data reveals that sales price, land area, floor area, number of bedrooms and number of bathrooms are all skewed to the right. Hence, the outliers were dropped using the following process for each school zone in each year. First, the bottom 1% and the top 3% of sales prices were dropped. Then, the top 1% of land were trimmed, followed by dropping the top 1% of floor areas. A further filtering step was taken to drop observations with number of bathrooms and number of bedrooms that are in the top 1% respectively. At the end of the trimming process, the sample is reduced to 9,209 observations. Finally, a further 3,638 observations with construction periods before 1950s were dropped. The final sample contains 5,657 observations for the period from 2007 to 2016.

Two land-related characteristics from QV's dataset are used in the main analysis: land area measured in square meters and school zone in which the land is located. Structure characteristics used in the main analysis include building age and square meters of floor

[13] 0.03% (5 observations) was on industrial land, 0.61% (109 observations) was on commercial land.
[14] 12 observations were for commercial use, and 1 was for other use.

area. QV's building age variable is coded in decade-long construction periods such as 1940s and 2010s. Following Diewert *et al.* (2015), age of the structure was recoded as the decade age using the following procedure. The most recent construction period for any houses sold in 2007 to 2009 was 2000s. Hence, the constructed decade age variable was set equal to $\frac{2000-\text{reported building age}}{10}$. From 2010 onwards, the newest houses sold were built in 2010s. Hence the corresponding decade age variable was set equal to $\frac{2010-\text{reported building age}}{10}$. After recoding, a house built in 2000s and sold between 2007 and 2009 has a decade age of 0; whereas a house built in 2000s that sold in 2010s has a decade age of 1. Table 2.1 presents descriptive statistics for the analytical sample. On average, houses transacted were built two decades ago. The sample mean selling price is 1,164,640 NZ dollars (NZ\$), with average land and floor area about 580 m^2 and 217 m^2 respectively.

The correlations of the selling price with land area, floor area, decade age, and total number of rooms are 0.3567, 0.6750, -0.1032,[15] and 0.4432, respectively. The correlation between land area and floor area is 0.2661. The correlations between of decade age with land area and floor area are 0.4656 and -0.3890 respectively, indicating that older houses have relatively larger land but smaller structural space. Moreover, the correlation between floor area and number of rooms is substantial at 0.6712. All of these correlation coefficients are statistically significant at the 0.05 level.

2.3.2 Land Slope Construction

The land slope used in this paper, as demonstrated in Figure 2.1, is created from a light detection and ranging (LiDAR) 1-meter resolution digital elevation model (DEM) fitted to

[15] Without excluding the construction period before 1950s, the correlation between selling price and decade age is 0.1811, indicating the possible vintage effects of older structures.

the map of New Zealand Primary Land Parcels using ArcGIS. Both maps are converted to New Zealand Transverse Mercator 2000 (NZTM2000) projection for analysis.

The airborne Auckland LiDAR 1m DEM data was captured in 2013 for Auckland Council by NZ Aerial Mapping & Aerial Surveying Limited. It was collected at more than 1.5 point/square meter point density. The 1m DEM data is downloaded via Land Information New Zealand (LINZ) Data Service.[16] Elevation values are in meters. In ArcGIS, the unit of measure for the z (elevation) unit is also meter, so the z-factor of value 1 is used to calculate the percentage values of slopes (the rate of change of elevation) in each DEM cell.[17]

The map of New Zealand Primary Land Parcels is also downloaded using LINZ Data service.[18] It provides information on parcel ID that is used to link parcels (sites) to addresses. To determine the terrain slope of each land parcel, the Zonal Statistic tools in ArcGIS was used. Each land parcel in the land parcel map is an input zone; the parcel ID is used to define the zones. The raster created from the 1m DEM containing the slope values is then used to calculate the mean slope for each zone (i.e. parcel). The result parcel slope map is presented in Figure 2.1. For reference, an aerial map of the study area is also shown in Figure 2.2. Table 2.1 shows that the average slope of the entire sample is 18.55% or 10.51°. The slopes are then divided into six broad groups according to the slope classes from Land Resource Information System (LRIS)[19] as shown in Table 2.2 - flat to gently undulating (0 - 3°), undulating (4 - 7°), rolling (8 - 15°), strongly rolling (16 - 20°) moderately steep (21 –

[16] More information about DEM can be found at: `https://data.linz.govt.nz/layer/53405-auckland-lidar-1m-dem-2013/`.

[17] There are two options for the units of measure for terrain slope: degree values and percentage values. Please see Appendix B.1 for more information.

[18] More information about NZ Primary Parcels can be found at: `https://data.linz.govt.nz/layer/50772-nz-primary-parcels/data/`.

[19] Please see Appendix B.1 for a range of slope classifications from different countries.

35°) and steep (26 - 35°) - to be used in the main analysis.[20] Table 2.3 shows that 41.7% of the sample is in the rolling slope range. The correlations of land slope with land area, floor area, and total number of rooms are 0.2285, 0.2148, and 0.1462, respectively.

2.3.3 Linking Parcels with Addresses

To link the computed land parcel slopes to housing addresses, the Address Component data from LINZ's Address Information Management System (AIMS) was used.[21] AIMS Address Component data contains information on address ID, parcel ID and components of each address such as address number, street number and road name. Parcel ID is used to link address data to the mean slope data. Components of each address are combined in the order of the provided address component order[22] to a single full address, which is then linked to the housing address in the QV data.

2.3.4 Building Outlines

There are four primary types of land ownerships in New Zealand that determine the property owner's rights: freehold, leasehold, unit title and cross lease. 99.6% of the final sample has freehold titles and the other 0.4% has cross lease titles. Freehold, also known as "fee simple," is the most common ownership type in New Zealand. With a freehold title, the property owner owns the land and almost anything built on the land. With a cross lease title, the property owner owns a share of the land with other cross lease holders and is provided with the footprint of the building s/he is entitled to occupy. The difference that land titles can make in the analysis can be presented as follows. Suppose two properties share a piece

---

20 Observations with slope more than 35°were also dropped from the final sample.

21 More information about AIMS Address Component data can be found at: `https://data.linz.govt.nz/table/53354-aims-address-component/data/`.

22 Please see Appendix B.2 for more information on component types and orders.

of uneven land; one is located on the more even and flat half, whereas the other is located on the more sloped half. In this situation, using the mean slope of the land parcel would be an overestimate of the slope for the property built on the flat side, and an underestimate of the slope for the property built on the more sloped side. Hence, it is necessary to drill down to estimate the slope of the portion of land that is covered by the structure. The NZ Building Outlines accessed via LINZ Data Service contains the visible roof-line edge of a building from aerial imagery. Slopes calculated from DEM data are then aggregated to the building outline level. However, this building outline dataset neither contains address ID nor similar identifiers that could be linked to the housing data. To proceed, the addresses were geocoded in the final analytical sample and then spatially joined to the building outline (polygon) that contains them. Thereafter, the mean slope of the building outline polygon that contains the address is assigned as the land slope for the property.

An issue with this approach is due to possible mismatches of the building outlines and the specific address. Manual corrections were made to reduce the number of mismatches as much as possible. Given the amount of correction involved and the mismatches remained, the estimation results using building outline slopes are presented in the Appendix Table B.4. The regression results presented in the next section are robust (in terms of signs and magnitudes of estimated coefficients and explanatory power of the model) notwithstanding the choice of input zone (land parcels or building outlines) for slopes.

2.4 Empirical Results

2.4.1 Exogenous Information on the Prices of Structures

The practical problem with models defined by equations (2.2) to (2.6) is that multicollinearity between land area and structure area results in highly unstable and unreasonable estimates. Empirical evidence (e.g., Diewert *et al.*, 2011, 2015; Diewert and Shimizu, 2016) suggests that an approach based on exogenous information on the price of structures can overcome the multicollinearity between land area and structure area and produce more reasonable and stable price dynamics for both land and structure. Such exogenous prices are usually new construction price indices reported by a statistical agency.[23] As indicated by Rosenthal (1999), the long run equilibrium price of new structures equals current construction costs.

The quarterly housing construction cost index is derived from Statistics New Zealand (Stats NZ) building consent statistics for new homes in the Auckland region. Building consent statistics contain information about the numbers, values and floor areas of new homes, non-residential buildings, and alterations approved for construction.[24] To construct the quarterly housing construction cost index γ_t, actual values of new homes approved for construction in quarter t in Auckland region are divided by floor areas of new homes approved

23 Models with straight-line depreciation, and with price of new structure growing proportionally to the exogenous construction cost index at a constant rate (i.e. $p_s^t = \theta\gamma_t$) were also estimated. Yet, these models' results were not satisfactory, which confirm the use of geometric depreciation and the use of exogenous construction cost index directly (i.e. $p_s^t = \gamma_t$).

24 More information about building consent can be found at: `https://www.stats.govt.nz/information-releases/building-consents-issued-may-2018`.

for construction in the same quarter in the Auckland region:

$$\gamma_t = \frac{\text{value value of new homes approved for construction}_t}{\text{floor area of new homes approved for construction}_t} \tag{2.7}$$

Quarterly building consent statistics for new houses in Auckland region are presented in Table 2.4. Quarterly construction indices calculated using equation (2.7) are presented in column (3); construction cost per square meter increased by about 56.76% from 2007 to 2016. These values are not inflation-adjusted.

2.4.2 Results of Builder's Models

Instead of estimating 40 standard builder's models defined in equation (2.3), one for each quarter starting from 2007 quarter 1 to 2016 quarter 4, the combined version of equation (2.3) was estimated with 40 quarterly dummies. The combined estimation allows the comparison of log-likelihood values across models. The results of the combined standard model are presented in column (1) of Table 2.5. In the combined standard model, there are 3 explanatory variables (land area, floor area, and decade house age) and 41 parameters (40 quarterly land prices and the net decade depreciation rate δ) to be estimated. The adjusted R-squared shows that the 3-predictor non-linear model explains 86.2% of variation in selling prices. The estimated 40 quarterly prices of land show that the land price increased 2.40-fold (normalized in column 2 of Table 2.6) over the 10 years, a much greater rate than the 1.57-fold (normalized in column 1 of Table 2.6) increase in construction cost index over the same time period. The estimated net decade depreciation rate δ is 0.074 or 7.4% per decade. This corresponds to an annual net depreciation rate of 0.74% per year, which is comparable to the annual net depreciation rates of the standard models in Diewert and Shimizu (2016) and the annual net depreciation rates on single family owner-occupied dwelling in Chinloy (1977).[25]

The standard and the generalized builder's models to be estimated are all nonlinear models that are estimated using iteration methods that require starting values for the parameters. To facilitate the convergence of the estimation algorithm for models with more parameters, estimates from the models with fewer parameters will be used as the stating values in the estimation of models with more parameters.

Using the estimated coefficients from the standard model as the initial values, the combined version of the generalized builder's model defined in equation (2.5) is estimated with school zones and numbers of rooms. To avoid the dummy variable trap, Selwyn college school zone and two-to-four-room group[26] serve as the reference groups receptively. Estimated results are presented in column (2) of Table 2.5. This non-linear model consists of 5 explanatory variables (land area, floor area, decade house age, school zone, number of rooms), and 47 parameters to be estimated. The adjusted R-squared shows that the 5-predictor model explains 93.8% of the variation in selling prices. Moreover, log-likelihood, AIC and BIC all indicate that adding two school zones and four number of rooms category variables as explanatory variables together results in a statistically significant improvement in model fit compared to the standard model. After controlling for additional structural and land characteristics, the estimated quarterly land prices point to a 2.82-fold increase (normalized in column 3 of Table 2.6) in land prices over the 10 years, compared to 2.40 in

[25] Diewert and Shimizu (2016) suggest that the annual net geometric depreciation rate is between 1% and 4%. Chinloy (1977) estimates an annual net geometric rate on single family, owner-occupied dwelling to be 0.69 − 0.91% in London.

[26] 4.55% (419 observations) of the data has two or three rooms. Hence, they are re-grouped with four rooms. The two-to-four-room group is set as the base group.

the standard model. In addition, the estimated decade net depreciation rate now is 6.4%[27].

This corresponds to a net annual depreciation rate of 0.64%. Everything else being equal, compared to per square meter construction cost for a two-to-four-room house, it costs about NZ$1100 more per square meter to build a five- or six-room house, and about NZ$1300 more per square meter to build a house with more than seven rooms. This is reasonable since, with more rooms, more building materials are required, and construction time may be extended. As a result, both the costs of material and labor will increase with number of rooms. This model also shows that, on average, land in the One Tree Hill College school zone is NZ$360 cheaper per square meter than in the Selwyn College zone, whereas land in the Double Grammar zone is more expensive than in Selwyn College school zone by NZ$552 per square meter. This is consistent with the market observation. The Double Grammar zone is the most sought-after state school zone in Auckland, with mean property values constantly reported to be hundreds of thousands of dollars higher than outside the enrollment zone. In addition, the enrollments in both Auckland Grammar and Epsom's Girl's Grammar have approached their maximum values, accompanied by an increase in school age residents in the Double Grammar zone. The high demand and almost saturated supply of a place in the two Grammar schools have combined to drive up property prices. According to the New Zealand Herald newspaper, the research exclusively released to them by Property Economics in New Zealand shows that the school zoning drives the development, rather than the converse.[28] Hence, the estimated higher per square meter land price in Double Grammar zone can be explained as the financial premium in the Double Grammar zone attributed to the increasing

27 Using number of bedrooms instead of number of rooms results in a net decade depreciation of 11.7%.
28 Pleaser refer to The New Zealand Herald article.

demand and the shortage of land within the zone.

Now turning to the generalized model incorporating land slope discussed above, the combined version of the model defined in equation (2.6) is estimated instead of estimating 40 separate models for each quarter. Estimated coefficients from the previous generalized model were used as the starting values. Since 41.7% of the observations were in the rolling slope range, the rolling slope category was set as the reference land slope category. Estimated results for the 52 parameters for the 6-predictor non-linear model are presented in column (3) of Table 2.5. The adjusted R-squared increased slightly to 0.940. Nonetheless, the log-likelihood, AIC and BIC all indicate that adding five site-slope parameters together does result in a statistically significant improvement in model fit compared to the previous generalized model without terrain slopes. After controlling for the slopes of land parcels, the estimated quarterly constant quality land indices show that land prices increased by 2.78-fold (normalized in column 4 of Table 2.6) over the 10 years, compared to 2.82 in previous model. Results for the decade net depreciation rate, school zones, number of rooms are consistent with previous estimates.

With additional land-slope parameters, this model suggests the confirmation of hypothesis 1 that per square meter land price decreases with land slope, indicating the difficulty to build with sloping land dominates the possible slope-associated views in terms of pricing. Flat to gently undulating land (0 - 3°) is on average more expensive than the rolling land (8 - 15°) by NZ$117 per square meter. The slightly positive price difference between undulating (4 - 7°) and rolling land, and the small negative price difference between strongly rolling (16 – 20°) and rolling land are not statistically significant. In contrast, moderately steep (21

– 25°) and steep (26 - 35°) land are cheaper by NZ$168, and NZ$268 per square meter in comparison with that of rolling land. As discussed in previous sections, the difficulty and complexity generated by building on land with steeper slopes is compensated by cheaper land prices.[29]

2.4.3 Construction of Overall House Price Index

The above model decomposed sales price into the constant quality price of land and constant quality price of structure. With several steps, they can be combined to generate the overall house price index. First, utilizing the estimates from the generalized builder's model with land slopes, imputed constant quality amount of land ($\widehat{IL}_{it}$) and imputed constant quality amount of structure $\widehat{IS}_{it}$) for each house i sold in quarter t can be constructed as follows:

$$\widehat{IL}_{it} = (1 + \sum_{z=1}^{Z} \widehat{\lambda}_z Zone_{it,z})(1 + \sum_{s=1}^{S} \widehat{\beta}_s \, Slope\ Group_{it,s}) L_{it} \tag{2.8}$$

$$\widehat{IS}_{it} = (1 - \hat{\delta})^{A_{it}} (1 + \sum_{r=1}^{R} \widehat{\eta}_r R_{it,r}) S_{it} \tag{2.9}$$

Then the total constant quality amount of land $\widehat{IL}_t$ and total constant quality amount of structure $\widehat{IS}_t$ in quarter t can be formed by aggregating $\widehat{IL}_{it}$ and $\widehat{IS}_{it}$ in that quarter separately.

$$\widehat{IL}_t = \sum_{i=1}^{N(t)} (1 + \sum_{z=1}^{Z} \widehat{\lambda}_z Zone_{it,z})(1 + \sum_{s=1}^{S} \widehat{\beta}_s \, Slope\ Group_{it,s}) L_{it} \tag{2.10}$$

$$\widehat{IS}_t = \sum_{i=1}^{N(t)} (1 - \hat{\delta})^{A_{it}} (1 + \sum_{r=1}^{R} \widehat{\eta}_r R_{it,br}) S_{it} \tag{2.11}$$

29 Estimation results using alternative land slope classification are presented in Appendix Table B.2 and are consistent with the main results.

To construct the overall house price index in quarter t, estimated constant quality land price in quarter t, $\widehat{p_t^L}$, is normalized such that land price index in quarter 1 is 1.

$$\widetilde{p_t^L} = \frac{\widehat{p_t^L}}{\widehat{p_1^L}} \tag{2.12}$$

The total constant quality amount of land $\widehat{IL}_t$ in quart t is rescaled accordingly to maintain the predicted constant quality of land values as follows:

$$\widetilde{IL}_t = \widehat{p_1^L} \cdot \widehat{IL}_t \tag{2.13}$$

Constant quality amount of structure prices and total constant quality amount of structures are normalized and rescaled in a similar way and presented in equations (2.14) and (2.15).

$$\widetilde{p_t^S} = \frac{\gamma_t}{\gamma_1} \tag{2.14}$$

$$\widetilde{IS}_t = \gamma_1 \cdot \widehat{IS}_t \tag{2.15}$$

The prices and quantities of aggregate constant quality of land and structures formed from equations (2.12) - (2.15) are used to construct Fisher (1921) house price indices. The Fisher index is chosen over Laspeyres and Paasche indices, for Laspeyres index is positively biased while Paasche is negatively biased. A similar procedure is used to form constant quality of land and structure indices and Fisher chained house price indices for the estimated standard builder's model and the generalized without land slopes.

Normalized constant quality of structure and land sub-indices from Tables 2.4 and 2.5 are presented in Table 2.6 together with the imputed Fisher chained aggregate house indices for all three models. Overall house price indices from the traditional hedonic model with time dummy variables and the structural and land controls (including land slope) used in the generalized builder's model are presented in column (8) of Table 2.6 for comparison.[30] Land and house price indices are also plotted in Figure 2.3. It appears that the standard builder's model (the model uses only land area, floor area and decade age) generates higher land price indices up to the fourth quarter of 2014 compared to those of generalized models. The generalized builder's models show that land price decreased by about 30% at the end of 2008 compared to 2007Q1, whereas structure construction cost increased by about 18% at the same time. This is consistent with the literature that structure price fluctuates less than land price and land and structure values evolve differently over time. Comparing land prices from the two generalized models, it appears that using land slope as an additional explanatory variable reduces the land price index in the last quarter by 4.57 percentage point (a decrease of 1.62%) in comparison with that of the generalized model without slopes. It can also be seen in panel (a) of Figure 2.3 that estimated land prices are almost identical in most quarters and differ moderately in several quarters. Care must be taken to interpret these results. Since land slope is found to discount house value (hypothesis 1), the minor changes in land price indices after controlling for land slope suggest the occurrence of case 2 that the slope compositions, and hence changes in land price indices, do not differ significantly over time controlling for slope. Indeed, at the significance level of 0.1, the hypothesis that the mean of land slope is the same for 2007Q1 and each of the subsequent quarters is only rejected in 2009Q4 and 2014Q1, among which the largest difference in mean slope is 1.26°.

30 The traditional hedonic model estimated takes the following form:

$$ln(p_{it}) = \alpha + \sum_{t=2}^{T} \delta_t D_{it} + \gamma_L ln(S_{it}) + \gamma_A ln(A_{it}) + \sum_{z=1}^{Z} \lambda_z Zone_{it,z} + \sum_{s=1}^{S} \beta_s Slope\ Group_{it,s} + \varepsilon_{it}$$

House price indices from the hedonic regression is then constructed as the exponential of $\hat{\delta}_t$.

Turing to the aggregate house price indices, Table 2.6 and panel (b) of Figure 2.3 show that on average the standard builder's model generates larger house price indices. The difference in the Fisher chained house price index in the last quarter between the two generalized models is 1.18 percentage point (a decrease of 0.5%). It can also be seen from panel (b) of Figure 2.3 that estimated house price indices from the traditional time dummy hedonic regression follow the Fisher chained house price indices from the generalized models closely up to the first quarter of 2015.

Our results from a small neighborhood in Auckland, New Zealand, where sloped terrain is common, show that land slope discounts (hypothesis 1) the unit land price. This result should not be directly generalized to other locations with sloped terrain. Instead, as discussed in section 2.3, there are two forces through which slope can affect the land price. Slope may discount land prices due to the complexity and cost to build, but it may also increase land prices for appreciable views. Which force dominates may depend on the local topography. For instance, in locations where slope can provide aesthetic advantages, like a spectacular view of lakes or mountains, it is reasonable to expect a price premium for sloping sites (hypothesis 2). With respect to quality-adjusted land price indices, our findings suggest that land slope has a negligible impact on quality-adjusted land price index when the composition of the slopes of houses sold remains stable over time (case 2) in the hilly area. Again, this should not be interpreted as land slope is of no importance for quality-adjusted land price indices. For example, as the subdivision of hilly areas becomes a problem in Los Angeles, there might be fewer houses built on sloping sites sold over time (case 1). Ignoring the variation in land slope composition would lead to biased land price indices.

2.5 Conclusion

The importance of separating structure and land has been well established but the difficulties of unbundling them remain in practice. Unlike structure, land is not reproducible; land parcels differ not only by location and size, but also slope and other topographical features. Hence, to form reliable constant quality land price indices requires controlling physical attributes of land that intrinsically confine the use of land and possibly discount land values.

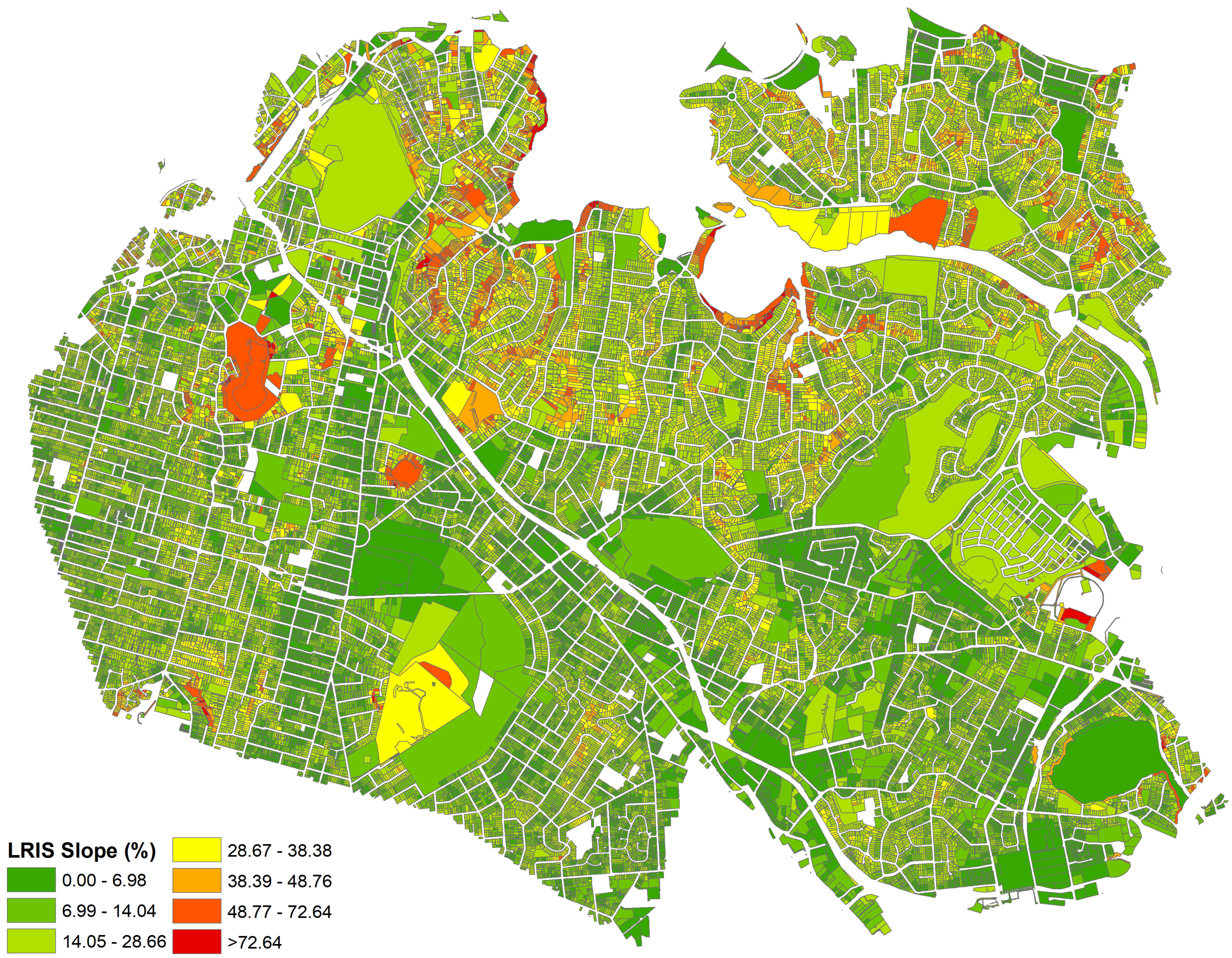
This paper endeavors to demonstrate that how a land-specific topographical characteristic - terrain slope - can be incorporated to builder's model. The analysis reveals a slope discount: lower per square meter price for land compensates for the difficulty and complexity to build as land slope increases. Constant quality land price indices from the generalize model decrease slightly about 4.57 percentage point (1.62% decrease) after controlling for land slopes. This difference may not seem notably large in magnitude but recall that the land slope compositions do not differ significantly over time, which seems to support that the use of the builder's model with only four explanatory variables - land area, location of the house, floor area and house age - generates credible overall house price indices and reasonable sub-price indices for land and structures. On the other hand, the moderate change in land price indices after including land slopes may due to the choice of a small sample. Recall that the study area only encompasses three neighboring school zones in Auckland. In this small study area, less than 6% of the land in One Tree Hill College zone has slopes above 15°. It is of interest to see its effect when applied to a larger spatial context with more observations in more sloped groups and a context with the composition of land slope changing over time. The official magazine of the Registered Master Builders Association (RMBA) in New Zealand, Building Today, reported in 2018 that although there continues to be strong demand for flat land, attention is turning to sloping land.[31] It might turn out that with more and more new houses built on sloping land over time, the effect of including land slope to construct quality adjusted land price indices may become more important.

The other limitation and possible extension come from the fact that the specification used is restrictive. It assumes that land price differences between school zones and across land slope classes do not change over time. On the contrary, land in the most sought-after school zones may appreciate more than others. Similarly, prices of less sloped land may increase faster over time than others due to scarcity especially in hilly regions. Thus, multiplicative interactions between the two variables and time may be important. In addition, sloping land can be subjected to higher risks of natural hazards. For example, the City of Christchurch experienced extensive liquefaction in 2010 and 2011 as a result of a series of large-scale earthquakes. Port Hills, the hilly part of the city, also experienced landslide and rockfalls. Hence, accounting for the interaction between land slope and risk of natural hazards would be an interesting topic for future research.

[31] Please refer to Building Today article.

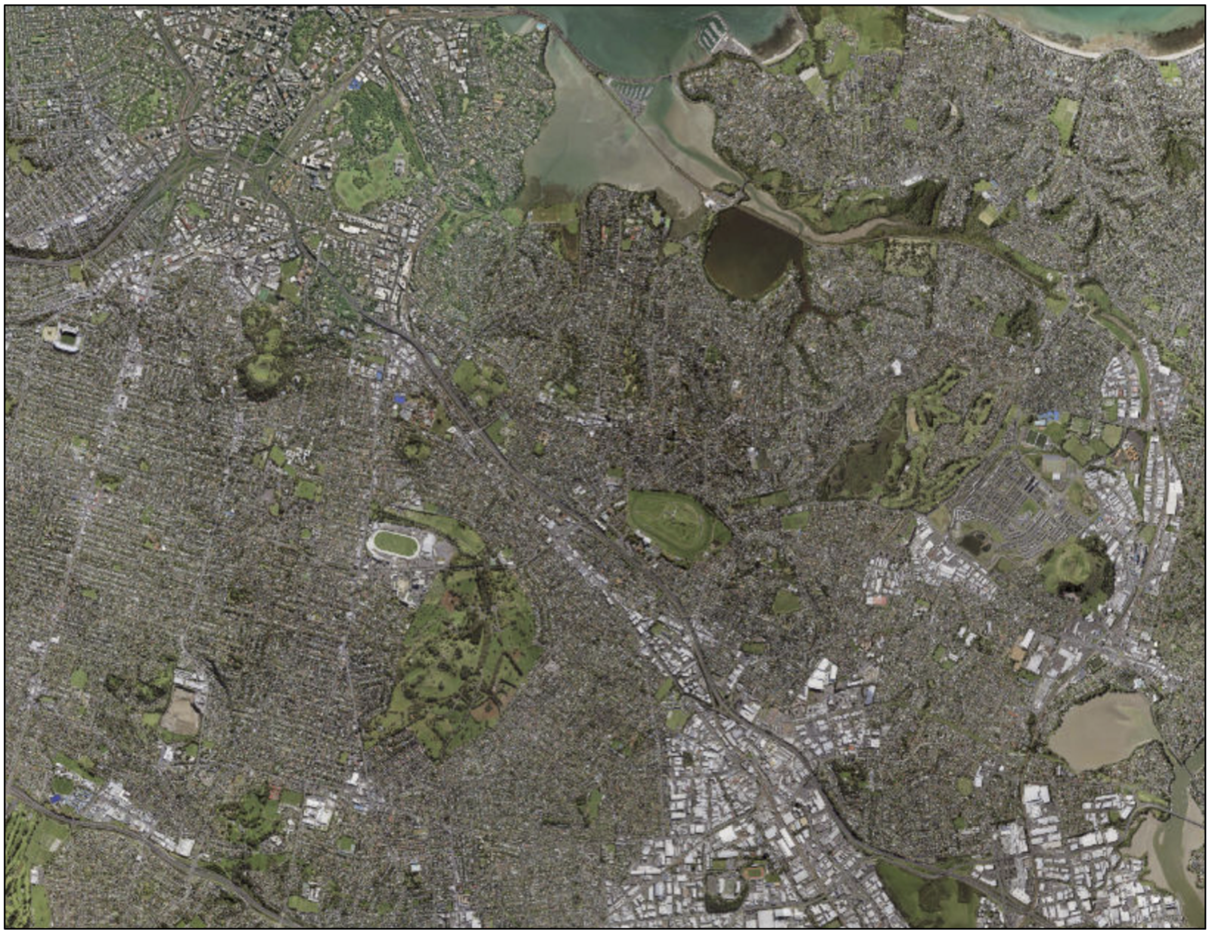
2.6 Figures and Tables

Figure 2.1: Land Parcel Slope in Percent Rise



Note: This map is produced by the authors in ArcGIS using 1m DEM fitted to the map of primary land parcels covering the study area.

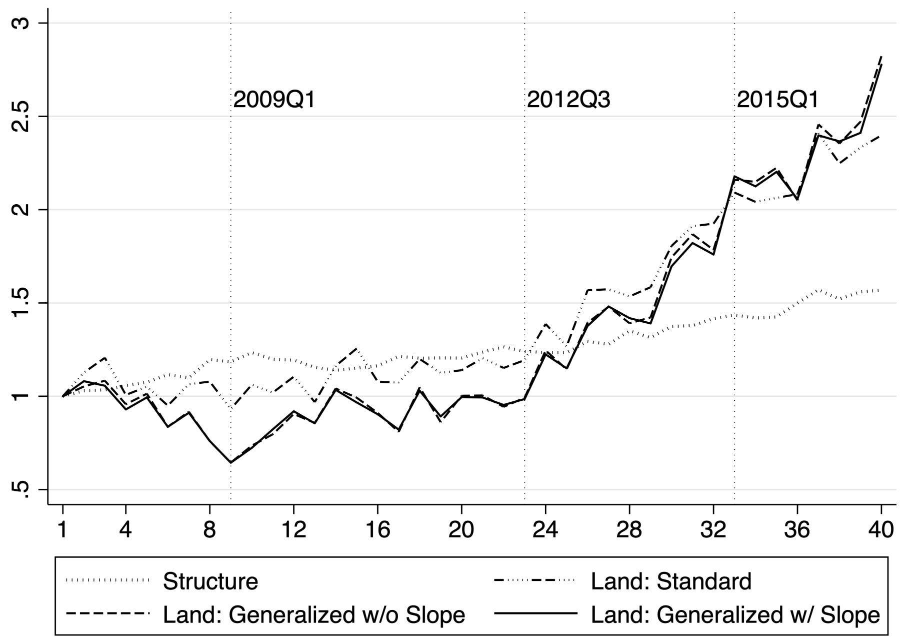
Figure 2.2: Aerial Imagery Reference of Study Area



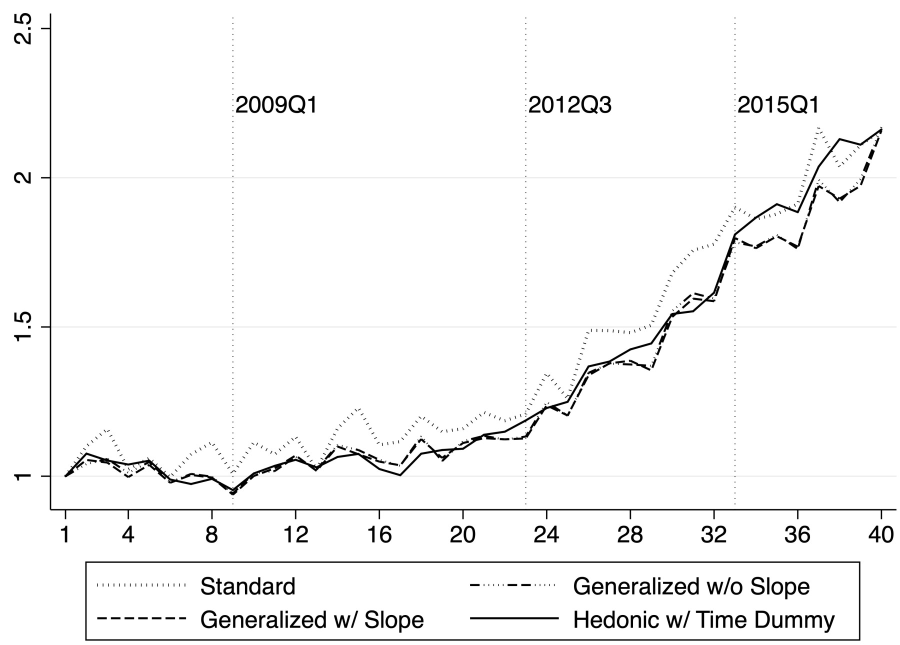
Source: Land Information New Zealand access from ArcGIS

Figure 2.3: Constant Quality Sub Price Indices and Aggregate House Price Indices

(a) Quarterly Constant Quality Sub Price Indices: 2007Q1 – 2016Q4



(b) Quarterly Aggregate House Price Indices: 2007Q1 – 2016Q4



Note: These figures present the normalized sub-price indices and aggregate house price indices displayed in Table 2.6.

Table 2.1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Selling Price (,000$)	1164.64	695.15	300.00	5880.00
Decade House Age	2.37	2.19	0.00	6.00
Land Area (m^2)	580.53	256.30	116.00	2048.00
Floor Area (m^2)	216.65	79.61	43.00	530.00
Bathrooms	1.98	0.89	1.00	5.00
Bedrooms	3.78	0.79	1.00	6.00
Land Slope (%)	18.55	12.05	1.53	69.57
Number of Observations		5,657		

Note: This table presents descriptive statistics for the selected neighborhoods in Auckland, New Zealand, from year 2007 to 2016. Land slope is measured in percent rise (%).

Table 2.2: New Zealand LRIS Slope Class

Slope Class	Degree°	Percent Rise(%)
Flat to gently undulating	0 - 3	0 - 6.98
Undulating	4 - 7	6.99 - 14.04
Rolling	8 - 15	14.05 - 28.66
Strongly rolling	16 - 20	28.67 - 38.38
Moderately steep	21 - 25	38.39 - 48.76
Steep	26 - 35	48.77 - 72.64
Very steep	36 - 42	72.65 - 90.04
Precipitous	> 42	> 90.04

Note: This table presents the LRIS slope class, accessible at Land Resource Information Systems (LRIS) Data Dictionary.

Table 2.3: Slope Class Frequency

LRIS Slope Class	Selwyn	One Tree Hill	Double Grammar	Total
Flat to gently undulating (0 - 3°)	7.01	21.14	11.49	12.21
Undulating (4 - 7°)	22.21	37.96	21.54	26.48
Rolling (8 - 15°)	46.52	34.83	40.93	41.70
Strongly rolling (16 - 20°)	14.53	4.63	12.79	11.26
Moderately steep (21 - 25°)	6.29	1.13	8.22	5.36
Steep (26 - 35°)	3.44	0.31	5.03	2.99
Total	100	100	100	100
Number of Observations		5,657		

Note: This table presents the frequency of LRIS slope class within each school enrollment zone in the study area.

Table 2.4: Quarterly Building Consent For New Houses - Auckland Region

Year	Quarter	Value $NZ\$$ (1)	Floor Area m^2 (2)	Construction Index $NZ\$/m^2$ (3)
2007	Q1	308,470,997	252,573	1,221
2007	Q2	300,770,306	239,233	1,257
2007	Q3	345,485,007	273,549	1,263
2007	Q4	351,445,145	272,177	1,291
2008	Q1	286,205,722	218,038	1,313
2008	Q2	246,163,735	180,682	1,362
2008	Q3	198,047,620	147,618	1,342
2008	Q4	174,633,586	119,527	1,461
2009	Q1	168,884,517	116,789	1,446
2009	Q2	168,796,144	112,015	1,507
2009	Q3	211,740,103	144,729	1,463
2009	Q4	265,322,840	182,055	1,457
2010	Q1	242,630,596	172,010	1,411
2010	Q2	278,702,453	200,389	1,391
2010	Q3	244,406,195	173,977	1,405
2010	Q4	219,308,410	154,478	1,420
2011	Q1	224,515,030	151,485	1,482
2011	Q2	216,079,500	146,956	1,470
2011	Q3	253,871,795	172,412	1,472
2011	Q4	289,341,990	196,760	1,471
2012	Q1	288,826,634	191,250	1,510
2012	Q2	302,402,403	195,794	1,544
2012	Q3	291,687,676	192,531	1,515
2012	Q4	374,062,098	248,169	1,507
2013	Q1	349,495,817	231,893	1,507
2013	Q2	416,242,630	263,492	1,580
2013	Q3	418,365,595	268,079	1,561
2013	Q4	424,108,493	257,157	1,649
2014	Q1	450,361,701	280,527	1,605
2014	Q2	462,789,605	275,864	1,678
2014	Q3	455,226,457	270,563	1,683
2014	Q4	498,182,013	288,158	1,729
2015	Q1	450,550,041	257,013	1,753
2015	Q2	505,478,008	291,640	1,733
2015	Q3	553,545,632	318,161	1,740
2015	Q4	611,276,364	334,010	1,830
2016	Q1	599,102,433	312,367	1,918
2016	Q2	676,609,794	364,616	1,856
2016	Q3	672,485,586	353,101	1,905
2016	Q4	575,858,608	300,845	1,914

Note: The quarterly housing construction cost index is derived from Statistics New Zealand (Stats NZ) building consent statistics for new homes in the Auckland region.

Table 2.5: Builder's Models: Estimation Results

	(1) Standard		(2) Generalized w/o Slope		(3) Generalized w/ Slope	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
2007Q1	0.980***	(0.060)	0.653***	(0.051)	0.692***	(0.054)
2007Q2	1.104***	(0.065)	0.687***	(0.061)	0.748***	(0.052)
2007Q3	1.182***	(0.094)	0.707***	(0.065)	0.731***	(0.068)
2007Q4	0.987***	(0.063)	0.625***	(0.049)	0.643***	(0.050)
2008Q1	1.030***	(0.090)	0.661***	(0.051)	0.688***	(0.054)
2008Q2	0.931***	(0.079)	0.546***	(0.043)	0.579***	(0.041)
2008Q3	1.043***	(0.104)	0.598***	(0.085)	0.631***	(0.090)
2008Q4	1.057***	(0.078)	0.495***	(0.053)	0.526***	(0.059)
2009Q1	0.913***	(0.068)	0.420***	(0.050)	0.446***	(0.054)
2009Q2	1.040***	(0.065)	0.480***	(0.047)	0.501***	(0.047)
2009Q3	0.999***	(0.060)	0.520***	(0.044)	0.569***	(0.041)
2009Q4	1.082***	(0.062)	0.590***	(0.042)	0.637***	(0.044)
2010Q1	0.949***	(0.061)	0.559***	(0.040)	0.592***	(0.040)
2010Q2	1.140***	(0.074)	0.680***	(0.055)	0.716***	(0.058)
2010Q3	1.231***	(0.086)	0.648***	(0.060)	0.669***	(0.064)
2010Q4	1.056***	(0.074)	0.594***	(0.057)	0.625***	(0.058)
2011Q1	1.051***	(0.076)	0.528***	(0.055)	0.568***	(0.053)
2011Q2	1.175***	(0.078)	0.684***	(0.064)	0.713***	(0.065)
2011Q3	1.103***	(0.074)	0.562***	(0.077)	0.617***	(0.064)
2011Q4	1.117***	(0.076)	0.654***	(0.067)	0.689***	(0.067)
2012Q1	1.179***	(0.071)	0.655***	(0.049)	0.688***	(0.049)
2012Q2	1.128***	(0.055)	0.616***	(0.044)	0.660***	(0.043)
2012Q3	1.169***	(0.057)	0.647***	(0.042)	0.682***	(0.046)
2012Q4	1.359***	(0.072)	0.813***	(0.042)	0.847***	(0.042)
2013Q1	1.241***	(0.064)	0.747***	(0.044)	0.796***	(0.044)
2013Q2	1.536***	(0.076)	0.910***	(0.050)	0.953***	(0.054)
2013Q3	1.541***	(0.083)	0.966***	(0.058)	1.025***	(0.060)
2013Q4	1.504***	(0.088)	0.908***	(0.061)	0.982***	(0.060)
2014Q1	1.552***	(0.077)	0.928***	(0.060)	0.962***	(0.062)
2014Q2	1.769***	(0.102)	1.138***	(0.076)	1.174***	(0.080)
2014Q3	1.873***	(0.100)	1.219***	(0.076)	1.261***	(0.079)
2014Q4	1.886***	(0.080)	1.164***	(0.055)	1.218***	(0.059)
2015Q1	2.049***	(0.122)	1.409***	(0.083)	1.508***	(0.082)
2015Q2	2.000***	(0.097)	1.403***	(0.071)	1.471***	(0.072)
2015Q3	2.021***	(0.095)	1.451***	(0.066)	1.524***	(0.066)
2015Q4	2.041***	(0.096)	1.338***	(0.064)	1.423***	(0.060)
2016Q1	2.360***	(0.142)	1.603***	(0.091)	1.660***	(0.093)
2016Q2	2.203***	(0.108)	1.536***	(0.082)	1.637***	(0.073)
2016Q3	2.285***	(0.106)	1.612***	(0.085)	1.669***	(0.085)
2016Q4	2.350***	(0.180)	1.842***	(0.143)	1.922***	(0.137)
Decade Discount Rate δ	0.074***	(0.020)	0.064***	(0.007)	0.066***	(0.007)
One Tree Hill School Zone			−0.360***	(0.015)	−0.398***	(0.014)
Double Grammar Zone			0.552***	(0.039)	0.536***	(0.036)
5 Rooms			1.083***	(0.041)	1.036***	(0.042)
6 Rooms			1.092***	(0.043)	1.061***	(0.043)
7 Rooms			1.288***	(0.046)	1.262***	(0.046)
8+Rooms			1.281***	(0.046)	1.230***	(0.047)
Flat to gently undulating (0-3°)					0.117***	(0.037)
Undulating (4-7°)					0.042	(0.027)
Strongly rolling (16-20°)					−0.038	(0.036)
Moderately steep (21-25°)					−0.168***	(0.035)
Steep (26-35°)					−0.268***	(0.044)
Adjusted R^2	0.862		0.938		0.940	
Log-Likelihood	-43198.376		-40949.968		-40852.527	
AIC	86478.751		81993.935		81809.053	
BIC	86751.018		82306.046		82154.367	
Number of Observations	5,657		5,657		5,657	

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimation results for three builder's models. Selwyn College school zone is the base school zone. 2-to-4-room category is set as the reference room group. Rolling land (8-15°) is the base land slope class. Robust Standard errors in parentheses.

Table 2.6: Constant Quality Sub-Price Indices and Aggregate House Price Indices

Quarter	Structure Price Indices	Land Price Indices Standard	Land Price Indices Generalized w/o Slope	Land Price Indices Generalized w/ Slope	Fisher Chained House Price Indices Standard	Fisher Chained House Price Indices Generalized w/o Slope	Fisher Chained House Price Indices Generalized w/ Slope	Hedonic House Price Indicies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2007Q1	1	1	1	1	1	1	1	1
2007Q2	1.0295	1.1269	1.0528	1.0809	1.1004	1.0407	1.0546	1.0757
2007Q3	1.0344	1.2062	1.0835	1.0564	1.1582	1.0576	1.0456	1.0525
2007Q4	1.0573	1.0072	0.9576	0.9294	1.0233	1.0113	0.9972	1.0391
2008Q1	1.0753	1.0513	1.0137	0.9939	1.0603	1.0476	1.0381	1.0521
2008Q2	1.1155	0.9500	0.8365	0.8360	0.9970	0.9801	0.9780	0.9889
2008Q3	1.0991	1.0644	0.9171	0.9116	1.0730	1.0077	1.0041	0.9739
2008Q4	1.1966	1.0786	0.7592	0.7603	1.1135	0.9985	0.9956	0.9912
2009Q1	1.1843	0.9314	0.6442	0.6440	1.0078	0.9424	0.9381	0.9535
2009Q2	1.2342	1.0620	0.7354	0.7234	1.1136	1.0098	1.0008	1.0093
2009Q3	1.1982	1.0197	0.7963	0.8227	1.0733	1.0173	1.0266	1.0347
2009Q4	1.1933	1.1048	0.9048	0.9197	1.1323	1.0652	1.0695	1.0551
2010Q1	1.1556	0.9688	0.8571	0.8550	1.0232	1.0221	1.0179	1.0296
2010Q2	1.1392	1.1631	1.0418	1.0338	1.1598	1.1047	1.0995	1.0645
2010Q3	1.1507	1.2562	0.9924	0.9669	1.2292	1.0877	1.0735	1.0747
2010Q4	1.1630	1.0780	0.9106	0.9035	1.1049	1.055	1.0489	1.0241
2011Q1	1.2138	1.0730	0.8095	0.8212	1.1160	1.0348	1.0364	1.0034
2011Q2	1.2039	1.1997	1.0477	1.0295	1.2012	1.1340	1.1243	1.0754
2011Q3	1.2056	1.1253	0.8615	0.8918	1.1491	1.0506	1.0614	1.0877
2011Q4	1.2048	1.1397	1.0028	0.9953	1.1592	1.1172	1.1112	1.0920
2012Q1	1.2367	1.2038	1.0043	0.9935	1.2139	1.1353	1.1274	1.1388
2012Q2	1.2645	1.1517	0.9435	0.9533	1.1856	1.1227	1.1236	1.1491
2012Q3	1.2408	1.1936	0.9918	0.9853	1.2086	1.1329	1.1266	1.1869
2012Q4	1.2342	1.3874	1.2457	1.2242	1.3451	1.2482	1.2373	1.2284
2013Q1	1.2342	1.2670	1.1442	1.1500	1.2600	1.2027	1.2034	1.2492
2013Q2	1.2940	1.5681	1.3941	1.3769	1.4887	1.3464	1.3381	1.3678
2013Q3	1.2785	1.5734	1.4799	1.4810	1.4878	1.3773	1.3782	1.3842
2013Q4	1.3505	1.5351	1.3909	1.4184	1.4810	1.3745	1.3869	1.4249
2014Q1	1.3145	1.5845	1.4226	1.3903	1.5058	1.3698	1.3545	1.4449
2014Q2	1.3743	1.8057	1.7444	1.6965	1.6808	1.5538	1.5338	1.5435
2014Q3	1.3784	1.9115	1.8683	1.8212	1.7568	1.6133	1.595	1.5527
2014Q4	1.4161	1.9249	1.7844	1.7596	1.7775	1.5952	1.5863	1.6149
2015Q1	1.4357	2.0916	2.1599	2.1785	1.9017	1.7835	1.798	1.8099
2015Q2	1.4193	2.0416	2.1494	2.1248	1.8613	1.7699	1.7637	1.8664
2015Q3	1.4251	2.0628	2.2243	2.2024	1.8782	1.8085	1.8041	1.9114
2015Q4	1.4988	2.0833	2.0503	2.0566	1.9125	1.7617	1.7692	1.8847
2016Q1	1.5708	2.4089	2.4568	2.3981	2.1669	1.9936	1.9724	2.0373
2016Q2	1.5201	2.2481	2.3541	2.3655	2.0373	1.9182	1.9301	2.1294
2016Q3	1.5602	2.3325	2.4709	2.4115	2.1093	1.9953	1.9729	2.1108
2016Q4	1.5676	2.3984	2.8225	2.7768	2.1593	2.1703	2.1585	2.1618

Note: This table presents the normalized land price indices, imputed Fisher Chained house price indices for each of the builder's models as well as structure price indices and hedonic house price indices. Hedonic house price indices in column (8) is calculated from the standard hedonic model with time dummy variables and the same structural and land characteristics from the generalized builder's model.

Chapter 3

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

3.1 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 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 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,

[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); Schwartz *et al.* (2014), and Bonilla-Mejía *et al.* (2020).

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., Des Rosiers *et al.*, 2000). 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 Colwell, 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 Guntermann and 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.*, 2000). More recently, Sah *et al.* (20) 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 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: section 3.2 describes Auckland's housing market and the selected geographic area of our study. Section 3.3 presents the empirical strategy, the hedonic model, and our quantile regressions. Section 3.4 describes the data and their source. Estimation results are presented and discussed in section 3.5. The last section summarizes the results and offers some concluding remarks.

3.2 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 Figure 3.1, AGS enrollment zone (orange) and EGGS enrollment zone (pink) overlap. The overlapped 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 3.1 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.

3.3 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:

$$logP_{it} = \sum_{k=1}^{K} \beta_k z_{it,k} + \sum_{t=1}^{T} \alpha_t D_{it} + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{3.1}$$

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; 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); 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 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:

$$\begin{aligned} logP_{it} &= \beta_1 dschool_{it} + \beta_2 dschool_{it}^2 + \beta_3 dcbd_{it} + \beta_4 dcbd_{it}^2 + \beta_5 (dschool_{it} \times dcbd_{it}) \\ &+ \beta_6 dshop_{it} + \beta_7 dbeach_{it} + \beta_8 dsmallpark_{it} + \beta_9 dmediumpark_{it} + \beta_{10} dlargepark_{it} \\ &+ \sum_{k=1}^{K} \alpha_k S_{it,k} + \sum_{t=1}^{T} \gamma_t DY_{it} + \sum_{p=1}^{P} \lambda_p DP_{it} + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \end{aligned} \tag{3.2}$$

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); 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 equation (3.2), the marginal effect of driving distance to school on log of house price is obtained as follows:

$$\frac{\partial logP_{it}}{\partial dschool_{it}} = \beta_1 + 2\beta_2 \times dschool_{it} + \beta_5 \times dcbd_{it} \tag{3.3}$$

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 β_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]:

$$\begin{aligned} logP_{it} = {} & \beta_1 dAGS_{it} + \beta_2 dAGS_{it}^2 + \beta_3 dEGGS_{it} + \beta_4 dEGGS_{it}^2 \\ & + \beta_5 (dAGS_{it} \times dcbd_{it}) + \beta_6 (dEGGS_{it} \times dcbd_{it}) + \sum_{a=7}^{13} \beta_a d_{it,a} \\ & + \sum_{k=1}^{K} \alpha_k S_{it,k} + \sum_{t=1}^{T} \gamma_t DY_{it} + \sum_{p=1}^{P} \lambda_p DP_{it} + \varepsilon_{it}, \quad i = 1, \ldots N, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \end{aligned} \tag{3.4}$$

[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.

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 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:

$$\frac{\partial logP_{it}}{\partial dAGS_{it}} = \beta_1 + 2\beta_2 \times dAGS_{it} + \beta_5 \times dcbd_{it} \tag{3.5}$$

In Eqs. (3.1) to (3.5) 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; 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; Koenker and Bilias, 2002) and education economics (e.g., Arias *et al.*, 2002; Levin, 2002).

The conditional quantile regression at the q^{th} quantile, the quantile version of equation (3.1), can be written as:

$$Q_{logP_{it}|z_{it},d_{it}}(q) = \sum_{k=1}^{K} \beta_k(q) z_{it,k} + \sum_{t=1}^{T} \alpha_t(q) D_{it} + \varepsilon_{it}, \quad i = 1, \dots N, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{3.6}$$

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.

3.4 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 3.1 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).

The list of shopping centers is provided in Appendix Table C.1. 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 C.2. 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 3.1 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 3.2. 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.*, 2000, 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 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.

3.5 Empirical Results

Equation (3.2) is estimated for Selwyn College and One Tree Hill College zones separately while equation (3.4) is estimated for DGZ. The results are presented in columns (1) to (6) of Tables 3.3 and 3.4. As expected, the coefficient estimates associated to the structural and site-specific characteristics (shown in Tables 3.3) 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, 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 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 3.4 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 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 equation (3.5), 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 equation (3.5). 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 3.2a and Figure 3.2b 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 3.2a indicates that the sales price decreases with the driving distance to AGS until about 3.664 km from the school and increases afterward. In Figure 3.2b, 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 3.4. 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 3.2e and Figure 3.2f 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 3.2e shows that the log of sales price decreases with driving time to AGS with slightly decreasing rate (i.e. decreasing and concave up). In Figure 3.2f, 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 3.4, column 3) shows that everything else being equal, driving distance to Selwyn College increases housing values but at a decreasing rate. Figure 3.2c 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 Figure 3.2g.

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 3.4, column 5, and Figure 3.2d). Figure 3.2d 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 Figure 3.2h, 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 3.4 and plots in Figure 3.2 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 Jr and Mendelsohn, 1984; 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 10^{th}, 50^{th}, and 90^{th} percentiles of the price distribution. Results based on defining distance as driving distance and driving time are reported in Tables 3.5 and 3.6, respectively. Quantile estimates are also presented in Figure 3.3 for each of the school zones. The quantile analysis plotted in Figure 3.3a reveals that the nonlinear return of proximity to AGS measured by driving distance is most prominent at the 10^{th} 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 10^{th}, 50^{th}, and 90^{th} percentiles respectively (it was 3.664 km in Figure 3.2a). An alternative measure of proximity, defined by driving time, affects the rates of nonlinear returns as shown in Figure 3.3e. Yet, it is still evident in Figure 3.3e that capitalization of proximity to AGS is most prominent at the lower quantile of the sales price distribution.

Figure 3.3b 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 50^{th} and 90^{th} 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 90^{th} percentile as plotted in Figure 3.3f.

For the Selwyn College zone, our quantile plots in Figure 3.3c and Figure 3.3g 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 Figure 3.3d suggest a milder nonlinear relation beyond the 4 km driving distance at the selected percentiles, whereas the relationship is only statistically significant in the 50^{th} percentile. The nonlinear effects and the negative effects of proximity to school are more noticeable when estimated using driving time (Figure 3.3h). That is to say, school proximity is more of a "nuisance" than a "benefit" for houses in One Tree Hill College zone.

3.6 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; Rosiers *et al.*, 2001; Theisen and Emblem, 2018.

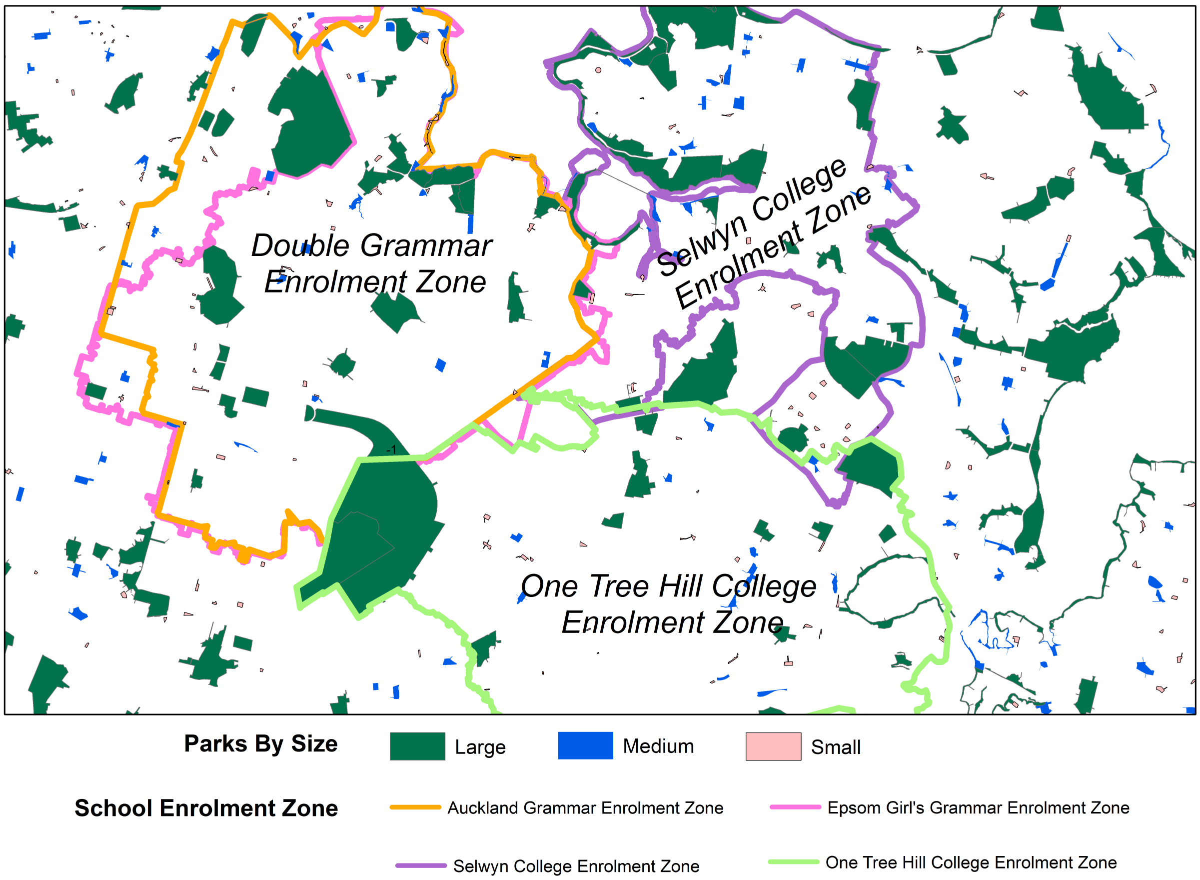
Based on a sample of housing sales recorded in the most sought-after school zone in Auckland, New Zealand, as well as in its two neighboring school zones, this paper provides evidence that everything else held constant, belonging to a school zone is certainly not the only feature that matters to homeowners. 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 10^{th} 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 10^{th} to the 90^{th} 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.

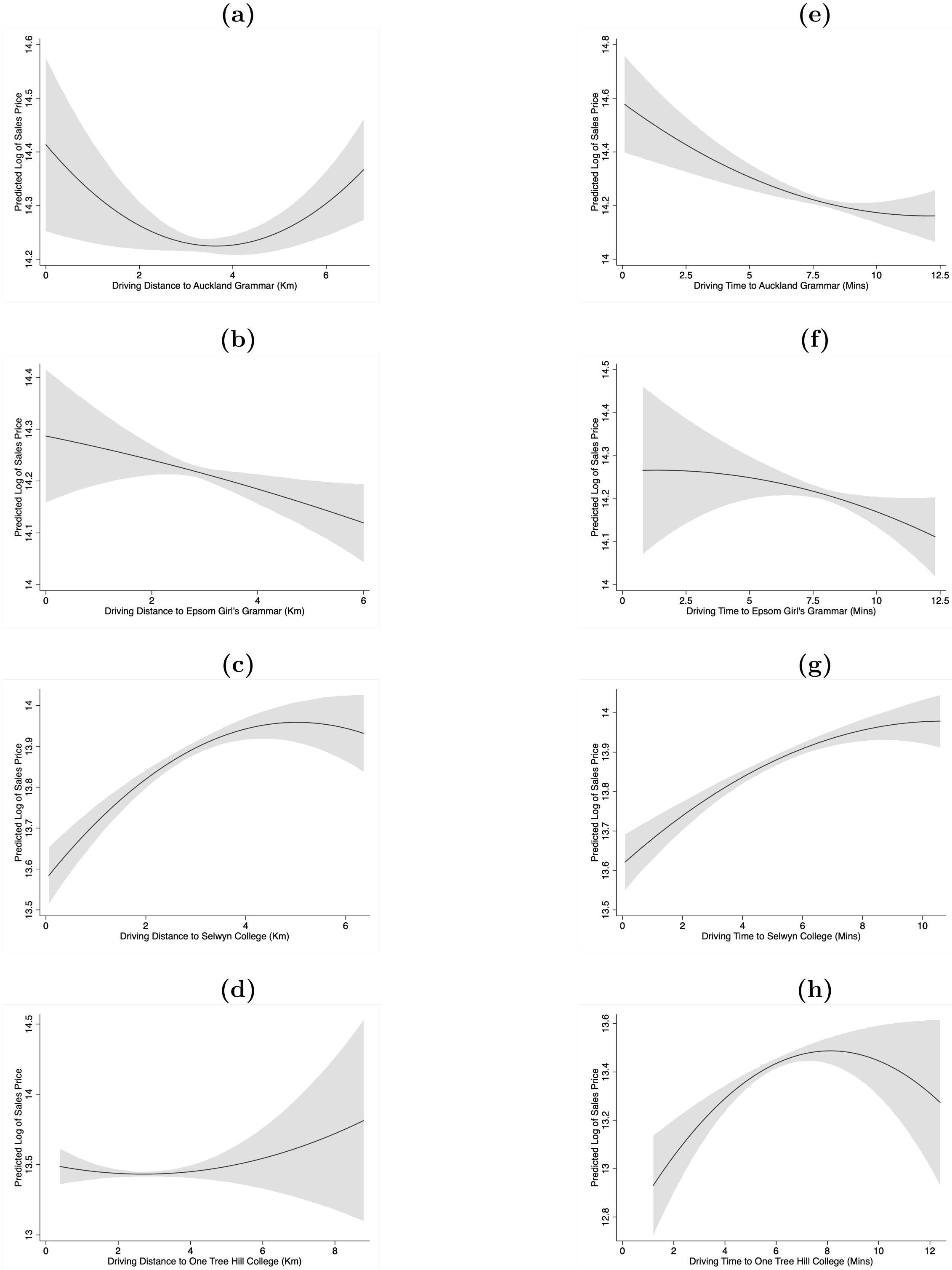
3.7 Figures and Tables

Figure 3.1: 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 Enrollment Scheme Master downloaded from Education Counts.

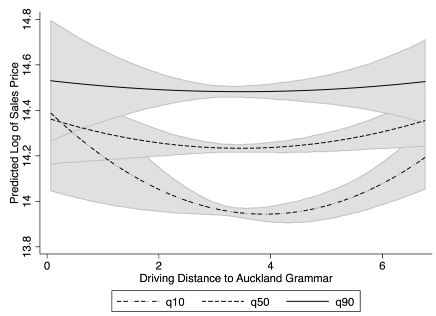
Figure 3.2: Predicted Log of Sales Price for Driving Distance(km)/Time(mins) to School



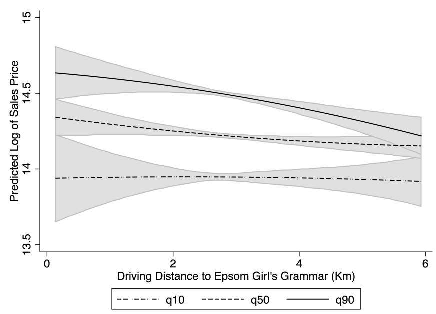
Note: These figures show the predicted values of log of sales price from the standard hedonic models and its 95% confidence band for the sample values of driving distances (km) and time (mins) in each school zone. Other variables were centered at their means for these plots.

Figure 3.3: Quantile Plots - Predicted Log of Sales Price for Driving Distance/Time to Schools

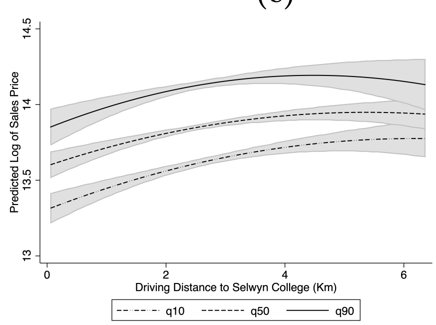
(a)



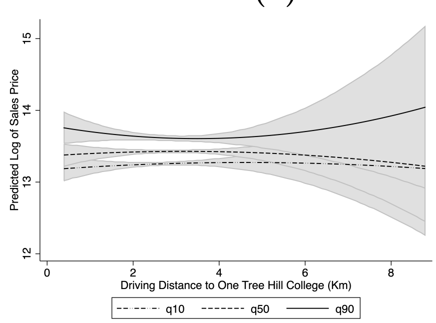
(b)



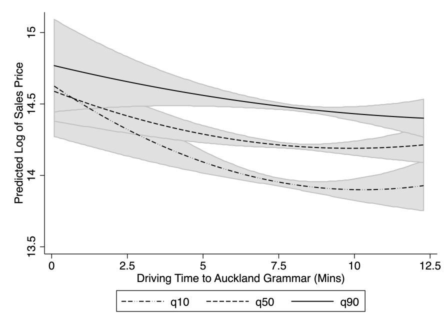
(c)



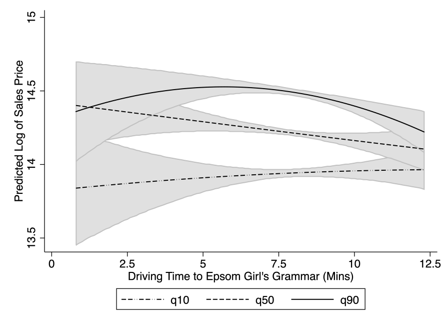
(d)



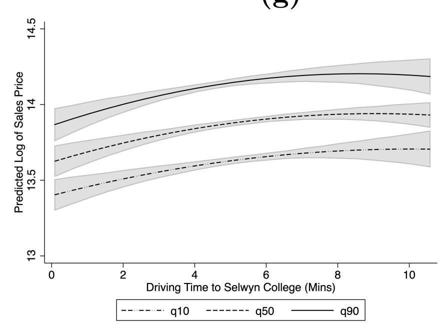
(e)



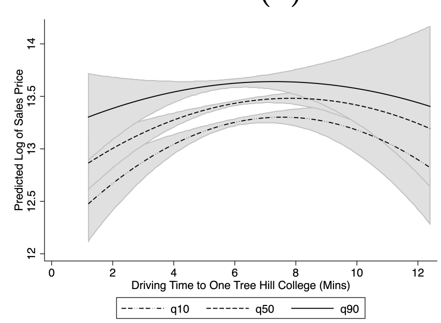
(f)



(g)



(h)



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 3.1: Pearson Product-Moment Correlations of Driving Distance and Driving Time

(a) Double Grammar Zone ($N = 3,037$)

Variable	1	2	3	4	5	6
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 ($N = 3,082$)

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***	0.227***	–	
4. Driving Time to CBD	-0.448***	-0.369***	0.701***	–

(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	0.730***	0.663***	–	
4. Driving Time to CBD	0.844***	0.859***	0.870***	–

Note: $^{*}p < .10$,$^{**}p < .05$,$^{***}p < .01$. 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.

Table 3.2: 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
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.

Table 3.3: 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)
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.

Table 3.4: Estimation Results: Proximity Controls

	Double Grammar		Selwyn College		One Tree Hill College	
	Distance (1)	Time (2)	Distance (3)	Time (4)	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)
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
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 prolixity controls from the standard henodic models. CBD represents Central Business District.

Table 3.5: 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)
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)
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 3.6: 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)
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)
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.

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Appendix A: Appendix of Chapter 1

A.1 Liquefaction Hazard in 2002 & 2005

Table A.1: Price Effects of 2002 Liquefaction Hazard Class

	Coef.	Std.Err.
Moderate	0.008	(0.016)
High	0.002	(0.015)
post2002	0.642***	(0.014)
Moderate × post2002	−0.002	(0.016)
High × post2002	−0.006	(0.012)
Adjusted R^2	0.694	
Number of Observations	13,707	
Baseline Mean $Log(P)$	11.90	

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Note: This table presents the effects of liquefaction hazard classes from the 2002 liquefaction study for log of property price for the City of Christchurch for the period 2000 – 2005. The reference class is the low hazard. Amenity controls, year, seasonal and area unit fixed effects are controlled for. Standard errors are clustered at area unit levels.

Three liquefaction hazard classes from the 2002 study were used: "Low: low liquefaction potential", "Moderate: moderate liquefaction potential", and "High: high liquefaction potential".

Table A.2: Price Effects of 2005 Liquefaction Hazard Class

	Summer		Winter		Joint	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Moderate	-0.052	(0.039)	-0.016	(0.017)	-0.043	(0.026)
High	-0.032	(0.033)	-0.006	(0.014)	-0.040	(0.025)
Low Uncertain	-0.134^{***}	(0.033)	-0.099^{***}	(0.037)	-0.167^{***}	(0.049)
Moderate Uncertain	-0.024	(0.037)	0.001	(0.036)	-0.113^{*}	(0.059)
High Uncertain	-0.331^{***}	(0.098)	-0.306^{***}	(0.088)	-0.347^{***}	(0.120)
post2005	0.605^{***}	(0.023)	0.618^{***}	(0.027)	0.593^{***}	(0.023)
Moderate × post2005	0.034^{*}	(0.020)	0.016	(0.024)	0.020	(0.016)
High × post2005	0.034^{*}	(0.020)	0.018	(0.020)	0.024	(0.017)
Low Uncertain × post2005	0.263^{***}	(0.070)	0.250^{***}	(0.070)	0.252^{***}	(0.063)
Moderate Uncertain × post2005	0.141^{**}	(0.057)	0.134^{**}	(0.061)	0.184^{**}	(0.085)
High Uncertain × post2005	0.487^{***}	(0.121)	0.475^{***}	(0.113)	0.483^{***}	(0.140)
Number of Observations	19,165		20,390		20,585	
Adjusted R^2	0.625		0.632		0.636	
Baseline Mean $Log(P)$			12.25			

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Note: This table presents the effects of liquefaction hazard classes from the 2005 liquefaction study for log of property price for the City of Christchurch for the period 2003 – 2008. The reference class is the low hazard. All models include amenity controls, year, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Six liquefaction hazard classes from the 2005 study were used: "Low: low liquefaction potential", "Moderate: moderate liquefaction potential", "High: high liquefaction potential", "Low uncertain: insufficient information available, but may have low liquefaction potential", "Moderate uncertain: insufficient information available, but may have moderate liquefaction potential", and "High uncertain: insufficient information available, but may have high liquefaction potential".

A.2 Define Relative Year to TC

The TC zoning was announcement on October 28, 2011. Relative year to TC was constructed as following:

Table A.3: Year to TC Announcement

Year relative to TC	Time Range	Earthquake Occurrence
-7	Jan 01, 2005 – Oct 27, 2005	
-6	Oct 28, 2005 – Oct 27, 2006	
-5	Oct 28, 2006 – Oct 27, 2007	
-4	Oct 28, 2007 – Oct 27, 2008	
-3	Oct 28, 2008 – Oct 27, 2009	
-2	Oct 28, 2009 – Oct 27, 2010	Sep 4, 2010 EQ
-1	Oct 28, 2010 – Oct 27, 2011	Feb 22 & Jun 13, 2011 EQs
1	Oct 28, 2011 – Oct 27, 2012	
2	Oct 28, 2012 – Oct 27, 2013	
3	Oct 28, 2013 – Oct 27, 2014	
4	Oct 28, 2014 – Oct 27, 2015	
5	Oct 28, 2015 – Oct 27, 2016	
6	Oct 28, 2016 – Oct 27, 2017	
7	Oct 28, 2017 – Dec 31, 2018	

A.3 Structural and Amenity Controls

This section presents a brief discussion on structural characteristics and distances to various amenities from the two standard hedonic models. Estimates are presented in columns (1) and (2) of Table A.4, respectively. Results show that the log of selling price increases with floor area (Appendix Figure A.1a), decreases with the log of land area till 5.7 (298.9m^2), and increase afterward (Appendix Figure A.1b). In general, houses built in the 2000s are valued the most. Houses built in the 1940s, 1950s, 2010s have the most significant discounts. Houses constructed in the 1940s and 1950s were about 12% less valued than otherwise similar houses built in the 2000s, respectively. This is because ,in response to the shortage of building materials such as copper, steel and paint ingredients for housing construction during the war periods, the New Zealand government introduced legislation to control the use of building materials in the 1940s, and also caused severe setbacks to the earthquake resistant design of timber houses.[4] Private dwellings in the 1940s and 1950s adhered to the designs of state housing (low-cost and small to today's standards), and insulation was installed in very few houses. Houses constructed in the 2010s also appeared to be valued less than otherwise similar houses built in the 2000s by 13%. This is possibly due to the change in the building code after the 2010-2011 earthquakes.

Houses with appreciable water views had price premiums as large as 8%, compared to houses without any appreciable views. This is consistent with the analysis of (20) that find price premiums for a water view in the three largest urban areas in New Zealand, among which Christchurch had the highest water view premium due to limited supply. Compared to houses with superior design and first-class quality of its era, houses with average design and quality valued 6% less, while houses with design and quality below average are worth about 25% less. Other structural characteristics generate standard results, with the price increasing with the number of bedrooms, bathrooms, and carparks.

[4] See Renovate.org.nz.

Turning to amenities, property values increase with distances to the CBD (Appendix Figure A.1c); decrease with distance to the Christchurch coast till 7 km and increase afterwards (Appendix Figure A.1d); decrease with distance to the nearest public hospital (Appendix Figure A.1e); decrease with distance to the nearest private hospital till 6 km and increase afterwards (Appendix Figure A.1f); and not vary significantly with distance to the nearest water body (Appendix Figure A.1g). Sizes and distances to each of the four types of parks are priced differently. Properties worth more being close to a large botanical garden and being away from a small sport park.

Table A.4: Structural and Amenity Controls from the Baseline Models

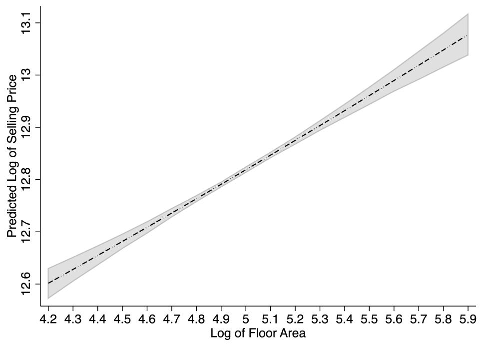
	(1) Model w/o dred		(2) Model w/ dred	
	Coef.	Std.Err.	Coef.	Std.Err.
Log of floor area	0.186	(0.198)	0.178	(0.194)
Log of floor area^2	0.009	(0.020)	0.010	(0.020)
Log of land area	−0.805***	(0.209)	−0.818***	(0.208)
Log of land area^2	0.071***	(0.016)	0.072***	(0.016)
Built in the 1910s	−0.076***	(0.015)	−0.081***	(0.015)
Built in the 1920s	−0.075***	(0.012)	−0.079***	(0.012)
Built in the 1930s	−0.072***	(0.012)	−0.077***	(0.012)
Built in the 1940s	−0.120***	(0.014)	−0.124***	(0.014)
Built in the 1950s	−0.124***	(0.013)	−0.127***	(0.013)
Built in the 1960s	−0.076***	(0.012)	−0.079***	(0.013)
Built in the 1970s	−0.071***	(0.014)	−0.073***	(0.014)
Built in the 1980s	−0.049***	(0.015)	−0.051***	(0.015)
Built in the 1990s	−0.003	(0.013)	−0.004	(0.012)
Built in the 2010s	−0.131***	(0.023)	−0.132***	(0.023)
Typical design and average quality of its era	−0.057***	(0.008)	−0.056***	(0.008)
Below average design and quality of its era	−0.251***	(0.013)	−0.249***	(0.013)
Appreciable View: Water View	0.082***	(0.022)	0.078***	(0.024)
Appreciable View: Other View	0.015	(0.011)	0.016	(0.011)
3 Bedrooms	0.045***	(0.005)	0.046***	(0.005)
4 Bedrooms	0.061***	(0.007)	0.062***	(0.007)
5 Bedrooms	0.069***	(0.010)	0.070***	(0.010)
2 Bathrooms	0.061***	(0.006)	0.060***	(0.006)
3 Bathrooms	0.087***	(0.011)	0.085***	(0.011)
2 Carparks	0.023***	(0.003)	0.023***	(0.003)
3 Carparks	0.022***	(0.006)	0.023***	(0.006)
4 Carparks	0.037***	(0.012)	0.040***	(0.012)
Roof: Steel	−0.009	(0.009)	−0.008	(0.009)
Roof: Tile	−0.003	(0.008)	−0.003	(0.008)
Wall: Brick	0.010	(0.008)	0.011	(0.008)
Wall: Concrete	0.010	(0.007)	0.010	(0.007)
Wall: Roughcast	0.016**	(0.008)	0.017**	(0.008)
Wall: Weatherboard	0.017**	(0.008)	0.018**	(0.008)
Wall: Mixed	−0.006	(0.009)	−0.006	(0.009)
Dist. from CBD (km)	0.078**	(0.034)	0.076**	(0.035)
Dist. from CBD^2	−0.002	(0.003)	−0.002	(0.003)
Dist. from Christchurch Coast (km)	−0.063***	(0.023)	−0.060**	(0.023)
Dist. from Christchurch Coast^2	0.004**	(0.002)	0.004**	(0.002)
Dist. from nearest regional park (km)	0.003	(0.016)	0.007	(0.016)
Nearest regional park size: medium	−0.040	(0.035)	−0.038	(0.031)
Nearest regional park size: large	−0.010	(0.020)	−0.006	(0.021)
Dist. from nearest regional park × medium	0.002	(0.008)	0.002	(0.007)
Dist. from nearest regional park × large	−0.012	(0.008)	−0.013*	(0.008)
Dist. from nearest botanical park (km)	−0.038**	(0.018)	−0.037*	(0.019)
Nearest botanical park size: medium	0.007	(0.022)	0.005	(0.021)
Nearest botanical park size: large	0.057***	(0.017)	0.055***	(0.018)
Dist. from nearest botanical park × medium	−0.014	(0.011)	−0.014	(0.011)
Dist. from nearest botanical park × large	−0.029***	(0.008)	−0.029***	(0.008)
Dist. from nearest community park (km)	0.022	(0.025)	0.023	(0.025)
Nearest community park size: medium	0.005	(0.011)	0.005	(0.011)
Nearest community park size: large	0.016	(0.011)	0.016	(0.011)
Dist. from nearest community park ×medium	−0.012	(0.037)	−0.011	(0.035)
Dist. from nearest community park × large	−0.034	(0.032)	−0.035	(0.031)
Dist. from nearest sports park (km)	0.040*	(0.021)	0.042*	(0.022)
Nearest sports park size: medium	0.030*	(0.017)	0.030*	(0.017)
Nearest sports park size: large	0.032*	(0.018)	0.032*	(0.018)
Dist. from nearest sports park × medium	−0.055*	(0.031)	−0.057*	(0.031)
Dist. from nearest sports park × large	−0.037	(0.027)	−0.039	(0.027)
Dist. from nearest public hospital (km)	0.026	(0.029)	0.027	(0.030)
Dist. from nearest public hospital^2	−0.007**	(0.003)	−0.007**	(0.003)
Dist. from nearest private hospital (km)	−0.151***	(0.052)	−0.140***	(0.052)
Dist. from nearest private hospital^2	0.012***	(0.004)	0.011***	(0.004)
Dist. from nearest water body (km)	0.047	(0.032)	0.044	(0.033)
Dist. from nearest water body^2	−0.019	(0.011)	−0.018	(0.012)
Elevation (m)	0.003	(0.003)	0.002	(0.003)
Constant	13.825***	(0.765)	13.837***	(0.840)

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

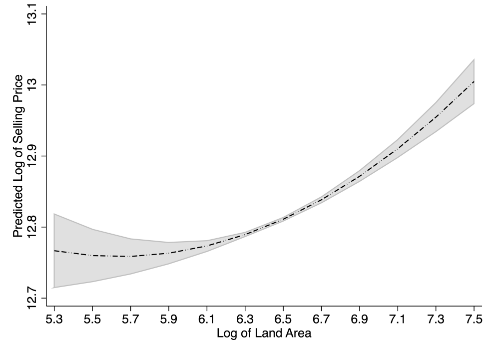
Note: This table presents the estimates of structural and amenity controls from the baseline regressions. Standard errors are clustered at area unit levels.

Figure A.1: Effects of Selected Controls on Predicted Log of Selling Price

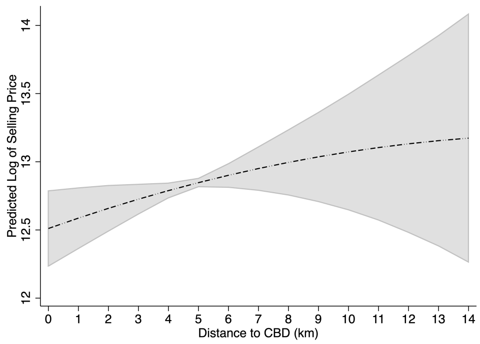
(a) Log of Floor Area



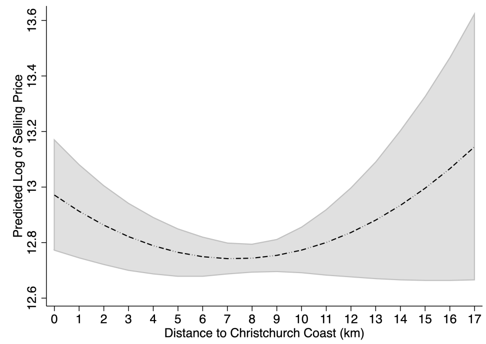
(b) Log of Land Area



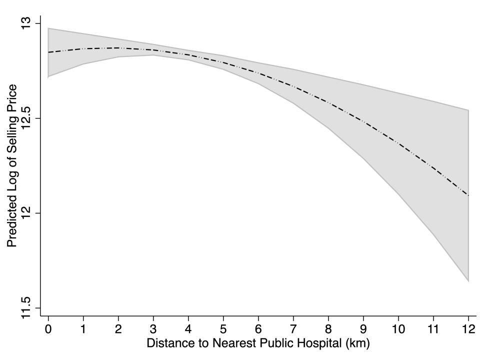
(c) Dist. from CBD



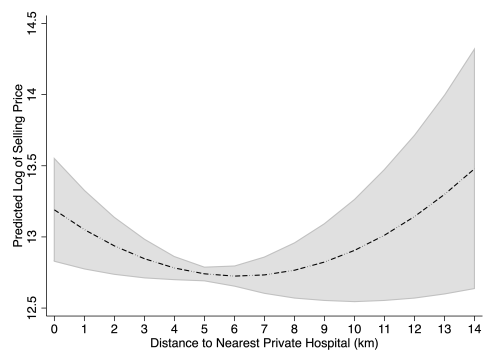
(d) Dist. from Christchurch Coast



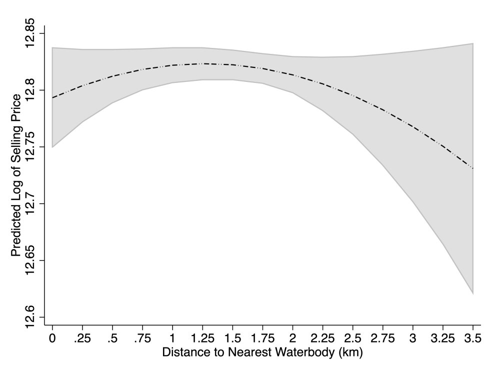
(e) Dist. from Nearest Public Hospital



(f) Dist. from Nearest Private Hospital



(g) Dist. from Nearest Water body



A.4 Effects on Shared Boundaries

Table A.5: Descriptive Statistics: Shared Boundaries of TC2 and TC3

	Before Oct 28, 2011			After Oct 28, 2011		
	TC2	TC3	Difference	TC2	TC3	Difference
Selling Price (NZ$)	352763.152	357674.424	-4911.271	455833.325	424296.888	31536.437***
Floor Area (m^2)	147.168	146.899	0.269	145.778	147.481	-1.703
Land Area (m^2)	650.700	672.754	-22.054***	658.562	672.316	-13.754***
Built in 1910s	0.049	0.040	0.010*	0.045	0.035	0.010*
Built in 1920s	0.164	0.179	-0.015	0.153	0.172	-0.019*
Built in 1930s	0.078	0.057	0.021***	0.071	0.060	0.010
Built in 1940s	0.091	0.072	0.019***	0.091	0.062	0.029***
Built in 1950s	0.116	0.139	-0.022***	0.120	0.124	-0.004
Built in 1960s	0.137	0.158	-0.021**	0.141	0.148	-0.007
Built in 1970s	0.075	0.095	-0.020***	0.084	0.092	-0.008
Built in 1980s	0.052	0.040	0.012**	0.049	0.042	0.007
Built in 1990s	0.066	0.071	-0.006	0.068	0.063	0.005
Built in 2000s	0.153	0.130	0.023***	0.100	0.092	0.008
Built in 2010s	0.018	0.020	-0.002	0.078	0.109	-0.031***
Superior design and first class quality	0.068	0.067	0.001	0.078	0.069	0.009
Average design and quality	0.899	0.854	0.045***	0.880	0.818	0.062***
Below Average design and quality	0.032	0.079	-0.047***	0.042	0.113	-0.071***
No appreciable view	0.972	0.956	0.016***	0.971	0.946	0.025***
Water View	0.007	0.015	-0.008***	0.005	0.022	-0.017***
Other than water View	0.021	0.029	-0.008*	0.023	0.032	-0.008*
1 or 2 Bedrooms	0.082	0.075	0.008	0.088	0.074	0.014**
3 Bedrooms	0.592	0.613	-0.021*	0.601	0.600	0.002
4 Bedrooms	0.282	0.278	0.004	0.273	0.289	-0.016
5 Bedrooms	0.043	0.034	0.009*	0.038	0.037	0.000
1 Bathrooms	0.689	0.690	-0.001	0.658	0.655	0.003
2 Bathrooms	0.276	0.270	0.006	0.300	0.302	-0.002
3 Bathrooms	0.035	0.040	-0.005	0.042	0.043	-0.001
1 Carparks	0.314	0.333	-0.018	0.316	0.311	0.004
2 Carparks	0.641	0.618	0.022*	0.642	0.641	0.001
3 Carparks	0.038	0.042	-0.004	0.040	0.045	-0.006
4 Carparks	0.007	0.007	0.000	0.003	0.002	0.001
Wall: Brick	0.239	0.234	0.005	0.254	0.201	0.053***
Wall: Concrete	0.192	0.220	-0.028***	0.192	0.210	-0.018*
Wall: Roughcast	0.149	0.148	0.001	0.145	0.159	-0.014
Wall: Weatherboard	0.320	0.320	-0.000	0.307	0.324	-0.017
Wall: Mixed Material	0.056	0.050	0.006	0.063	0.073	-0.010
Wall: Other	0.044	0.028	0.016***	0.038	0.032	0.006
Roof: Steel/G-Iron	0.589	0.557	0.032**	0.573	0.578	-0.005
Roof: Tile Profile	0.379	0.419	-0.040***	0.352	0.359	-0.008
Roof: Other	0.032	0.024	0.008*	0.035	0.023	0.012***
Dist. from CBD (km)	3.529	3.684	-0.155***	3.475	3.603	-0.128**
Dist. from Christchurch Coast (km)	5.414	5.252	0.163**	5.314	5.020	0.293***
Dist. from the nearest Public Hospital (km)	3.446	3.478	-0.032	3.451	3.496	-0.045
Dist. from the nearest Private Hospital (km)	4.196	4.177	0.019	4.246	4.251	-0.005
Dist. from the nearest Regional Park (km)	1.972	1.852	0.120***	1.965	1.859	0.106***
Dist. from the nearest Botanical Park (km)	1.593	1.692	-0.099***	1.578	1.702	-0.124***
Dist. from the nearest Community Park (km)	0.235	0.245	-0.010**	0.228	0.246	-0.018***
Dist. from the nearest Sports Park (km)	0.404	0.400	0.004	0.410	0.403	0.007
Dist. from the nearest Water Body (km)	1.215	1.240	-0.025	1.192	1.205	-0.013
Dist. from the nearest Residential Red Zone (km)	2.355	2.225	0.129***	2.294	2.050	0.244***
Elevation (m)	7.543	7.207	0.336***	7.410	6.898	0.512***
Number of Observations	3,641	2,652	6,293	3,169	2,728	5,897

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents summary statistics on the shared boundaries of TC2 and TC3 for Jan 1, 2005, to Oct 27, 2011 (Before period), and Oct 28, 2011, to Dec 31, 2018. Standard errors are clustered at area unit levels.

Table A.6: Dynamic Effects on the Shared Boundaries of TC2 and TC3

	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
TC3 × -7	0.009	(0.028)	0.026	(0.038)
TC3 × -6	−0.003	(0.016)	−0.009	(0.024)
TC3 × -5	−0.029	(0.022)	−0.006	(0.030)
TC3 × -4	−0.031	(0.021)	0.006	(0.029)
TC3 × -3	−0.012	(0.023)	−0.013	(0.030)
TC3 × -1	0.002	(0.024)	−0.051	(0.036)
TC3 × 1	−0.033	(0.027)	-0.088^{**}	(0.042)
TC3 × 2	-0.134^{***}	(0.036)	-0.213^{***}	(0.050)
TC3 × 3	-0.166^{***}	(0.031)	-0.242^{***}	(0.042)
TC3 × 4	-0.160^{***}	(0.030)	-0.169^{***}	(0.045)
TC3 × 5	-0.123^{***}	(0.027)	-0.144^{***}	(0.040)
TC3 × 6	-0.122^{***}	(0.025)	-0.175^{***}	(0.041)
TC3 × 7	-0.111^{***}	(0.019)	-0.115^{***}	(0.029)
TC3 × dred × -7			−0.007	(0.009)
TC3 × dred × -6			0.004	(0.006)
TC3 × dred × -5			−0.011	(0.010)
TC3 × dred × -4			−0.016	(0.010)
TC3 × dred × -3			−0.001	(0.008)
TC3 × dred × -1			0.022^{*}	(0.011)
TC3 × dred × 1			0.023^{**}	(0.011)
TC3 × dred × 2			0.040^{**}	(0.017)
TC3 × dred × 3			0.036^{**}	(0.013)
TC3 × dred × 4			0.007	(0.011)
TC3 × dred × 5			0.012	(0.010)
TC3 × dred × 6			0.028^{*}	(0.015)
TC3 × dred × 7			0.003	(0.008)
AdjustedR^2	0.667		0.672	
AIC	62.208		-134.423	
Number of Observations	12,190			
Baseline Mean $log(P)$	12.78			

$^{*}p < .10,^{**}p < .05,^{***}p < .01$

Note: This table presents the dynamic effects of TC on the shared boundaries of TC2 and TC3 for log of property price for the City of Christchurch for the period 2005–2018. The reference group is TC2 and the reference transaction time is 2 years before TC announcement (Oct 28, 2009 – Oct 27, 2010). Both models include amenity controls, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Table A.7: Descriptive Statistics: Shared Boundaries of TC1 and TC2

	Before Oct 28, 2011			After Oct 28, 2011		
	TC1	TC2	Difference	TC1	TC2	Difference
Selling Price (NZ$)	365591.140	382920.073	-17328.933	520211.566	542395.385	-22183.819
Floor Area (m^2)	148.077	152.251	-4.174	143.195	154.218	-11.023*
Land Area (m^2)	691.826	713.458	-21.632	696.950	745.321	-48.371**
Built in 1910s	0.000	0.006	-0.006	0.000	0.000	0.000
Built in 1920s	0.010	0.000	0.010	0.006	0.000	0.006
Built in 1930s	0.010	0.006	0.004	0.000	0.006	-0.006
Built in 1940s	0.029	0.056	-0.027	0.019	0.051	-0.032
Built in 1950s	0.333	0.235	0.099**	0.415	0.218	0.197***
Built in 1960s	0.435	0.436	-0.001	0.354	0.449	-0.065
Built in 1970s	0.005	0.073	-0.068***	0.013	0.064	-0.052**
Built in 1980s	0.029	0.028	0.001	0.044	0.051	-0.007
Built in 1990s	0.019	0.067	-0.048**	0.038	0.026	0.012
Built in 2000s	0.106	0.089	0.017	0.057	0.109	-0.052*
Built in 2010s	0.024	0.006	0.019	0.025	0.026	-0.000
Superior design and first class quality	0.097	0.117	-0.021	0.088	0.147	-0.059
Average design and quality	0.903	0.877	0.026	0.906	0.840	0.066*
Below Average design and quality	0.000	0.006	-0.006	0.006	0.013	-0.007
No appreciable view	1.000	0.966	0.034**	0.994	0.936	0.058***
Water View	0.000	0.011	-0.011	0.000	0.019	-0.019*
Other than water View	0.000	0.022	-0.022**	0.006	0.045	-0.039**
1 or 2 Bedrooms	0.048	0.050	-0.002	0.019	0.051	-0.032
3 Bedrooms	0.599	0.598	0.001	0.660	0.596	0.064
4 Bedrooms	0.300	0.302	-0.002	0.264	0.301	-0.037
5 Bedrooms	0.053	0.050	0.003	0.057	0.051	0.005
1 Bathrooms	0.700	0.654	0.047	0.755	0.660	0.094*
2 Bathrooms	0.246	0.318	-0.072	0.189	0.308	-0.119**
3 Bathrooms	0.053	0.028	0.025	0.057	0.032	0.025
1 Carparks	0.251	0.223	0.028	0.333	0.237	0.096*
2 Carparks	0.691	0.743	-0.052	0.623	0.737	-0.115**
3 Carparks	0.048	0.028	0.020	0.038	0.019	0.019
4 Carparks	0.010	0.006	0.004	0.006	0.006	-0.000
Wall: Brick	0.356	0.419	-0.023	0.434	0.423	0.011
Wall: Concrete	0.314	0.257	0.057	0.277	0.282	-0.005
Wall: Roughcast	0.111	0.117	-0.006	0.088	0.109	-0.021
Wall: Weatherboard	0.101	0.134	-0.033	0.138	0.115	0.023
Wall: Mixed Material	0.072	0.050	0.022	0.063	0.051	0.012
Wall: Other	0.005	0.022	-0.018	0.000	0.019	-0.019*
Roof: Steel/G-Iron	0.435	0.408	0.027	0.365	0.436	-0.071
Roof: Tile Profile	0.541	0.575	-0.034	0.597	0.532	0.065
Roof: Other	0.024	0.017	0.007	0.038	0.032	0.006
Dist. from CBD (km)	4.828	4.714	0.114	4.675	4.845	-0.171
Dist. from Christchurch Coast (km)	11.226	11.114	0.112*	11.135	11.181	-0.046
Dist. from the nearest Public Hospital (km)	4.822	4.736	0.086	4.580	4.922	-0.341*
Dist. from the nearest Private Hospital (km)	3.737	3.557	0.180***	3.715	3.601	0.114*
Dist. from the nearest Regional Park (km)	3.727	3.858	-0.131	3.877	3.700	0.177
Dist. from the nearest Botanical Park (km)	1.180	1.238	-0.058	1.163	1.281	-0.119***
Dist. from the nearest Community Park (km)	0.235	0.262	-0.027*	0.220	0.266	-0.046***
Dist. from the nearest Sports Park (km)	0.276	0.310	-0.034**	0.278	0.280	-0.003
Dist. from the nearest Water Body (km)	1.066	1.072	-0.005	1.134	1.053	0.081
Dist. from the nearest Residential Red Zone (km)	6.155	6.001	0.154**	6.070	6.085	-0.014
Elevation (m)	17.976	17.469	0.507***	17.799	17.596	0.203
Number of Observations	207	179	386	159	156	315

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents summary statistics on the shared boundaries of TC1 and TC2 for Jan 1, 2005, to Oct 27, 2011 (Before period), and Oct 28, 2011, to Dec 31, 2018. Standard errors are clustered at area unit levels.

Table A.8: Dynamic Effects on the Shared Boundaries of TC1 and TC2

	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
TC2 × -7	0.034	(0.047)	0.548	(0.335)
TC2 × -6	0.014	(0.025)	0.133	(0.276)
TC2 × -5	0.007	(0.062)	0.921^{**}	(0.309)
TC2 × -4	0.097	(0.061)	1.463^{***}	(0.426)
TC2 × -3	0.081	(0.059)	−0.008	(0.378)
TC2 × -1	0.036	(0.055)	0.134	(0.375)
TC2 × 1	−0.006	(0.066)	−0.154	(0.570)
TC2 × 2	−0.013	(0.059)	−0.062	(0.544)
TC2 × 3	−0.019	(0.022)	0.589^{**}	(0.238)
TC2 × 4	0.067	(0.059)	0.195	(0.516)
TC2 × 5	−0.063	(0.045)	−0.135	(0.448)
TC2 × 6	−0.009	(0.038)	0.488^{*}	(0.254)
TC2 × 7	0.039	(0.063)	1.281^{***}	(0.334)
TC2 × dred × -7			−0.086	(0.052)
TC2 × dred × -6			−0.019	(0.044)
TC2 × dred × -5			-0.149^{**}	(0.048)
TC2 × dred × -4			-0.227^{***}	(0.068)
TC2 × dred × -3			0.017	(0.057)
TC2 × dred × -1			−0.010	(0.059)
TC2 × dred × 1			0.027	(0.095)
TC2 × dred × 2			0.009	(0.086)
TC2 × dred × 3			-0.100^{**}	(0.041)
TC2 × dred × 4			−0.020	(0.082)
TC2 × dred × 5			0.010	(0.069)
TC2 × dred × 6			-0.082^{*}	(0.042)
TC2 × dred × 7			-0.204^{***}	(0.053)
Adjusted R^2	0.807		0.813	
AIC	-864.431		-920.148	
Number of Observations	701			
Baseline Mean $log(P)$	12.85			

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Note: This table presents the dynamic effects of TC on the shared boundaries of TC1 and TC2 for log of property price for the City of Christchurch for the period 2005–2018. The reference group is TC1 and the reference transaction time is 2 years before TC announcement (Oct 28, 2009 – Oct 27, 2010). Both models include amenity controls, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

Table A.9: Descriptive Statistics for Matching with 1 Nearest Neighbor: Shared Boundaries of TC2 and TC3

Variable	Before Oct 28, 2011					After Oct 28, 2011				
	Mean			t-test		Mean			t-test	
	TC3	TC2	%bias	t	$p > t$	TC3	TC2	%bias	t	$p > t$
Structural Characteristics:										
Selling Price (NZ$)	356,397	352,763	0.1	0.05	0.962	432,848	455,833	−10.5	−3.75	0.000***
Floor Area (m^2)	146.62	147.7	−2.0	−0.71	0.480	146.68	146.22	0.9	0.31	0.756
Land Area (m^2)	667.87	663.05	2.7	0.96	0.337	664.44	667.77	−1.7	−0.61	0.542
Built in 1910s	.041	.042	−0.4	−0.13	0.895	.038	.039	−0.7	−0.24	0.810
Built in 1920s	.172	.181	−2.3	−0.81	0.418	.158	.159	−0.3	−0.11	0.912
Built in 1930s	.058	.063	−2.2	−0.81	0.418	.064	.059	1.8	0.64	0.524
Built in 1940s	.075	.064	4.0	1.55	0.122	.067	.065	0.6	0.23	0.820
Built in 1950s	.138	.127	3.1	1.08	0.280	.119	.132	−3.9	−1.34	0.179
Built in 1960s	.158	.154	1.2	0.43	0.670	.149	.152	−0.9	−0.33	0.744
Built in 1970s	.093	.086	2.6	0.89	0.376	.089	.096	−2.3	−0.78	0.437
Built in 1980s	.042	.046	−1.9	−0.69	0.492	.044	.042	1.0	0.35	0.730
Built in 1990s	.069	.070	−0.3	−0.12	0.907	.056	.067	−4.6	−1.67	0.095*
Built in 2000s	.134	.144	−3.0	−1.07	0.285	.099	.094	1.8	0.64	0.521
Built in 2010s	.021	.024	−2.0	−0.67	0.504	.117	.094	7.9	2.63	0.009***
Superior design and first class quality	.070	.070	−0.3	−0.12	0.905	.072	.074	−1.0	−0.37	0.714
Average design and quality	.886	.883	1.1	0.41	0.685	.897	.872	7.0	2.75	0.006***
Below Average design and quality	.044	.047	−1.2	−0.48	0.634	.031	.053	−8.4	−3.90	0.000***
No appreciable view	.965	.964	0.3	0.12	0.903	.963	.966	−1.7	−0.66	0.509
Water View	.008	.010	−1.7	−0.65	0.514	.005	.007	−1.3	−0.68	0.495
Other than water View	.027	.026	0.7	0.25	0.806	.032	.027	3.0	1.04	0.299
1 or 2 Bedrooms	.076	.076	0.1	0.03	0.975	.074	.076	−0.8	−0.30	0.761
3 Bedrooms	.616	.599	3.5	1.23	0.219	.606	.621	−3.2	−1.12	0.263
4 Bedrooms	.274	.289	−3.3	−1.18	0.238	.282	.269	2.9	1.03	0.303
5 Bedrooms	.034	.036	−1.2	−0.43	0.670	.038	.033	2.5	0.89	0.375
1 Bathrooms	.690	.690	0.1	0.03	0.977	.649	.659	−2.0	−0.70	0.482
2 Bathrooms	.270	.273	−0.6	−0.23	0.819	.308	.295	2.8	0.98	0.328
3 Bathrooms	.040	.037	1.3	0.46	0.646	.043	.046	−1.6	−0.55	0.581
1 Carparks	.329	.311	4.0	1.41	0.159	.307	.321	−3.2	−1.13	0.259
2 Carparks	.621	.641	−4.1	−1.44	0.149	.652	.636	3.4	1.19	0.236
3 Carparks	.042	.040	1.0	0.37	0.715	.040	.040	−0.4	−0.16	0.873
4 Carparks	.007	.008	−1.1	−0.37	0.708	.002	.002	−0.8	−0.27	0.786
Wall: Brick	.240	.220	4.8	1.73	0.084	.203	.239	−8.7	−3.08	0.002***
Wall: Concrete	.221	.216	1.3	0.45	0.654	.210	.212	−0.6	−0.19	0.847
Wall: Roughcast	.147	.156	−2.5	−0.90	0.370	.157	.149	2.2	0.79	0.432
Wall: Weatherboard	.312	.318	−1.3	−0.46	0.645	.319	.304	3.2	1.14	0.256
Wall: Mixed Material	.050	.058	−3.4	−1.21	0.225	.076	.065	4.5	1.56	0.118
Wall: Other	.029	.032	−1.6	−0.60	0.546	.035	.031	2.3	0.83	0.406
Roof: Steel/G-Iron	.561	.580	−4.0	−1.41	0.158	.580	.559	4.1	1.45	0.146
Roof: Tile Profile	.415	.398	3.4	1.20	0.232	.395	.418	−4.7	−1.64	0.101
Roof: Other	.025	.022	1.9	0.74	0.457	.025	.023	1.5	0.56	0.573
Distance-based amenity characteristics:										
Distance to CBD (km)	3.676	3.616	2.9	1.03	0.302	3.560	3.551	0.5	0.16	0.869
Distance to Christchurch Coast (km)	5.280	5.437	−5.4	−1.90	0.058*	5.100	5.263	−5.6	−1.97	0.049***
Distance to the nearest Public Hospital (km)	3.479	3.445	2.0	0.71	0.479	3.487	3.453	2.0	0.71	0.476
Distance to the nearest Private Hospital (km)	4.160	4.280	−5.7	−2.02	0.043***	4.199	4.314	−5.4	−1.90	0.058*
Distance to the nearest Regional Park (km)	1.849	1.938	−6.3	−2.26	0.024***	1.853	1.913	−4.2	−1.53	0.126
Distance to the nearest Botanical Park (km)	1.676	1.643	2.4	0.83	0.406	1.658	1.628	2.1	0.74	0.462
Distance to the nearest Community Park (km)	.246	.234	6.6	2.32	0.020***	.247	.228	10.0	3.54	0.000***
Distance to the nearest Sports Park (km)	.401	.403	−0.7	−0.26	0.796	.398	.410	−4.5	−1.62	0.105
Distance to the nearest Water Body (km)	1.252	1.224	3.7	1.31	0.192	1.233	1.182	7.0	2.45	0.014**
Distance to the nearest Residential Red Zone (km)	2.244	2.403	−8.2	−2.88	0.004***	2.077	2.285	−10.9	−3.82	0.000***

Note: This table compares the mean on the shared boundaries of TC2 and TC3 for the matched sample obtained by nearest neighbor matching with 0.2 caliper width on structural characteristics, without replacement.

Table A.10: Descriptive Statistics for Matching with 1 Nearest Neighbor: Shared Boundaries of TC1 and TC2

Variable	Before Oct 28, 2011					After Oct 28, 2011				
	Mean			t-test		Mean			t-test	
	TC2	TC1	%bias	t	$p > t$	TC2	TC1	%bias	t	$p > t$
Structural Characteristics:										
Selling Price (NZ$)	362,218	365,182	−11.3	−0.99	0.324	511,892	509,159	1.8	0.14	0.889
Floor Area (m^2)	143.35	150.03	−13.6	−1.19	0.236	141.3	141.78	−0.9	−0.08	0.940
Land Area (m^2)	689.26	701.35	−7.6	−0.67	0.503	700.5	705.58	−3.0	−0.27	0.791
Built in 1910s	0	0	0.0	.	.	0	0	.	.	.
Built in 1920s	0	0	0.0	.	.	0	0	0.0	.	.
Built in 1930s	.008	.015	−8.2	−0.56	0.576	.009	0	15.9	0.99	0.325
Built in 1940s	.030	.044	−7.0	−0.61	0.545	.036	.028	4.5	0.35	0.730
Built in 1950s	.301	.228	16.2	1.35	0.177	.288	.278	2.3	0.17	0.864
Built in 1960s	.489	.493	−0.8	−0.06	0.949	.486	.519	−6.5	−0.47	0.637
Built in 1970s	0	.007	−3.9	−0.99	0.324	0	.019	−9.7	−1.44	0.151
Built in 1980s	.023	.022	0.3	0.03	0.978	.027	.028	−0.4	−0.03	0.973
Built in 1990s	.030	.029	0.3	0.03	0.975	.009	.046	−21.2	−1.69	0.092*
Built in 2000s	.113	.147	−11.5	−0.83	0.405	.126	.056	25.6	1.82	0.070*
Built in 2010s	.008	.015	−5.9	−0.56	0.576	.018	.028	−6.2	−0.48	0.631
Superior design and first class quality	.075	.110	−11.3	−0.99	0.323	.081	.120	−12.2	−0.96	0.336
Average design and quality	.925	.890	11.2	0.99	0.323	.919	.870	14.6	1.17	0.243
Below Average design and quality	0	0	0.0	.	.	0	.009	−9.5	−1.01	0.312
No appreciable view	1	1	0.0	.	.	1	.991	5.1	1.01	0.312
Water View	0	0	0.0	.	.	0	0	0.0	.	.
Other than water View	0	0	0.0	.	.	0	.009	−5.9	−1.01	0.312
1 or 2 Bedrooms	.045	.051	−2.9	−0.24	0.809	.045	.028	9.4	0.68	0.498
3 Bedrooms	.654	.610	8.9	0.74	0.458	.667	.685	−3.8	−0.29	0.771
4 Bedrooms	.248	.294	−10.0	−0.85	0.358	.261	.269	−1.6	−0.12	0.904
5 Bedrooms	.053	.044	3.8	0.32	0.746	.027	.019	3.8	0.42	0.675
1 Bathrooms	.737	.654	17.6	1.47	0.143	.757	.769	−2.6	−0.20	0.839
2 Bathrooms	.233	.316	−18.5	−1.53	0.128	.207	.185	5.1	0.41	0.683
3 Bathrooms	.030	.029	0.3	0.03	0.975	.036	.046	−5.0	−0.35	0.704
1 Carparks	.248	.235	3.0	0.24	0.807	.297	.352	−12.1	−0.86	0.351
2 Carparks	.707	.699	1.8	0.15	0.883	.694	.602	19.8	1.42	0.156
3 Carparks	.038	.051	−7.2	−0.55	0.583	.009	.037	−16.8	−1.39	0.167
4 Carparks	.008	.015	−8.2	−0.56	0.576	0	.009	−11.6	−1.01	0.312
Wall: Brick	.444	.397	9.5	0.77	0.441	.432	.398	6.9	0.51	0.609
Wall: Concrete	.293	.331	−8.3	−0.66	0.507	.297	.306	−1.8	−0.13	0.895
Wall: Roughcast	.075	.118	−13.3	−1.18	0.240	.090	.083	2.3	0.18	0.860
Wall: Weatherboard	.158	.125	10.2	0.77	0.441	.135	.176	−12.2	−0.83	0.407
Wall: Mixed Material	.030	.022	3.3	0.41	0.681	.045	.037	3.4	0.30	0.767
Wall: Other	0	.007	−6.4	−0.99	0.324	0	0	0.0	.	.
Roof: Steel/G-Iron	.383	.441	−11.7	−0.96	0.338	.432	.407	5.1	0.37	0.709
Roof: Tile Profile	.609	.551	11.6	0.95	0.341	.523	.574	−10.4	−0.76	0.446
Roof: Other	.008	.007	0.1	0.02	0.987	.045	.019	14.4	1.11	0.267
Distance-based amenity characteristics:										
Dist. from CBD (km)	4.773	4.822	−5.2	−0.42	0.678	4.902	4.772	13.8	1.04	0.299
Dist. from Christchurch Coast (km)	11.151	11.227	−12.5	−0.99	0.321	11.214	11.203	1.8	0.13	0.893
Dist. from the nearest Public Hospital (km)	4.869	4.801	4.4	0.36	0.719	5.065	4.766	19.2	1.49	0.137
Dist. from the nearest Private Hospital (km)	3.555	3.747	−34.9	−2.68	0.008***	3.590	3.680	−17.2	−1.18	0.240
Dist. from the nearest Regional Park (km)	3.721	3.759	−2.9	−0.23	0.815	3.559	3.765	−15.8	−1.20	0.230
Dist. from the nearest Botanical Park (km)	1.272	1.177	24.6	2.05	0.041**	1.326	1.172	42.2	3.26	0.001***
Dist. from the nearest Community Park (km)	.257	.251	4.3	0.34	0.736	.265	.219	31.7	2.26	0.025**
Dist. from the nearest Sports Park (km)	.315	.262	34.6	2.88	0.004***	.297	.273	15.1	1.16	0.246
Dist. from the nearest Water Body (km)	1.061	1.066	−1.0	−0.09	0.931	1.063	1.052	2.2	0.17	0.862
Dist. from the nearest Residential Red Zone (km)	6.029	6.158	−20.8	−1.61	0.109	6.107	6.100	1.2	0.08	0.936

Note: This table compares the mean on the shared boundaries of TC1 and TC2 for the matched sample obtained by nearest neighbor matching with 0.2 caliper width on structural characteristics, without replacement.

Table A.11: DID for Matching with 1 Nearest Neighbor: Shared Boundaries

	Coef.	Std.Err.	Coef.	Std.Err.
Panel A: TC2 vs TC3				
TC3 × post1	0.043	(0.031)	0.044	(0.030)
TC3 × post2	−0.025	(0.049)	−0.005	(0.049)
TC3 × post3	−0.038	(0.046)	−0.058	(0.047)
TC3 × post4	−0.072**	(0.029)	−0.109***	(0.032)
dred(km)			−0.039	(0.027)
dred × post4			0.016***	(0.005)
TC3 × dred			−0.008***	(0.003)
TC3 × dred × post4			0.018***	(0.004)
Adjusted R^2	0.667		0.671	
AIC	-295.215		-423.845	
Number of Observations		11,805		
Baseline Mean $log(P)$		12.70		
Panel B: TC1 vs TC2				
TC2 × post1	−0.070	(0.085)	−0.061	(0.083)
TC2 × post2	0.065	(0.083)	0.053	(0.078)
TC2 × post3	0.012	(0.066)	0.014	(0.067)
TC2 × post4	−0.039	(0.069)	−0.102	(0.140)
dred(km)			−5.800	(4.045)
dred × post4			−0.036	(0.027)
TC2 × dred			−0.047	(0.030)
TC2 × dred× post4			0.010	(0.022)
Adjusted R^2	0.800		0.801	
AIC	-765.773		-771.897	
Number of Observations		607		
Baseline Mean $log(P)$		12.77		

$^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

Note: This table presents the DID estimates on the shared boundaries. It covers years 2005 to 2018. The reference TC is TC2 and TC1 in panels A and B, respectively. All models include amenity controls, year, seasonal and area unit fixed effects. Standard errors are clustered at area unit levels.

The sample in each panel is obtained by propensity score matching using the nearest neighbor with 0.2 caliper width on the whole set of structural attributes.

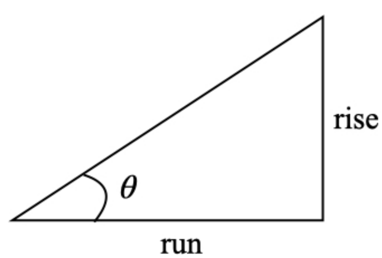
Appendix B: Appendix of Chapter 2

B.1 Slope

A slope is the rise or fall of the land. It is important for the builder to identify the slopes on the land since sloped land can be challenging to work on. Mathematically, the slope of a piece of land is expressed as "the rise over the run", where the rise is the vertical difference (difference in height/elevation) between two points in the land area, and the run is the horizontal distance between these two points.

$$\text{slope} = \frac{\text{rise}}{\text{run}} = \frac{\text{vertical difference}}{\text{horizontal distance}}$$

The percent rise (%) slope is then computed as slope$\times$100. The degree (°) of slope is $\boldsymbol{\theta}$.



The tables on the next page show a range of slope classifications used in different countries and different settings.

Table B.1: Classification of Land Slopes

(a) Slopes Commonly Used in Irrigated Fields

Slope Class	%	°
Horizontal	0 - 2	0 - 1.15
Very Flat	2 - 5	1.15 - 2.86
Flat	5 - 10	2.86 - 5.71
Moderate	10 - 25	5.71 - 14.03
Steep	> 25	> 14.03

http://www.fao.org/3/r4082e/r4082e04.htm

(b) Government of Canada Soil Landscape of Canada

Slope Class	%	°
Little or None	0 - 3	0 - 1.72
Gentle	4 - 9	2.29 - 5.14
Moderate	10 - 15	5.71 - 8.53
Steep	16 - 30	9.09 - 16.70
Extremely steep	31 - 60	17.22 - 30.96
Excessively steep	> 60	> 30.96

http://sis.agr.gc.ca/cansis/nsdb/slc/v3.2/cmp/slope.html

(c) Tweed Shire Council Australia Dwelling Houses

Slope Class	%	°
Flat	0 - 10.51	0 - 6
Moderate	10.51 - 21.26	6 - 12
Steep	21.26 - 32.49	12 - 18
Extremely Steep	> 32.49	> 18

https://www.tweed.nsw.gov.au/Download.aspx?Path=~/Documents/Planning/TSC02931_Fact_Sheet_4_Working_with_Sloping_Sites.pdf

(d) China Urban Construction Suitability

Slope Class	%	°
Flat	0.3 - 2	0 - 1.15
Little	2 - 5	1.15 - 2.86
Gentle	5-10	2.86 - 5.71
Moderate	10 - 25	5.71 - 14.03
Steep	25 - 50	14.03 - 26.67

https://wenku.baidu.com/view/504c9a10227916888486d79a.html

Note: This table presents a range of slope classifications used in different countries and different settings. % is the percent rise of slope. °is the degree of slope. The source data for panels (a) (b) and (c) provides slope in the percent rise, whereas the source data for panel (c) provides slopes in degree.

Table B.2: Estimation Results with Alternative Land Slope Class

	Generalized w/ Slope	
	Coef.	Std.Err.
2007Q1	0.717***	(0.054)
2007Q2	0.766***	(0.051)
2007Q3	0.736***	(0.068)
2007Q4	0.658***	(0.051)
2008Q1	0.698***	(0.052)
2008Q2	0.582***	(0.043)
2008Q3	0.648***	(0.090)
2008Q4	0.543***	(0.060)
2009Q1	0.453***	(0.055)
2009Q2	0.505***	(0.048)
2009Q3	0.573***	(0.044)
2009Q4	0.645***	(0.045)
2010Q1	0.604***	(0.041)
2010Q2	0.724***	(0.059)
2010Q3	0.683***	(0.064)
2010Q4	0.634***	(0.059)
2011Q1	0.583***	(0.055)
2011Q2	0.727***	(0.065)
2011Q3	0.636***	(0.061)
2011Q4	0.695***	(0.068)
2012Q1	0.699***	(0.049)
2012Q2	0.676***	(0.043)
2012Q3	0.692***	(0.046)
2012Q4	0.861***	(0.043)
2013Q1	0.809***	(0.045)
2013Q2	0.972***	(0.052)
2013Q3	1.039***	(0.060)
2013Q4	0.995***	(0.061)
2014Q1	0.993***	(0.062)
2014Q2	1.208***	(0.081)
2014Q3	1.278***	(0.082)
2014Q4	1.231***	(0.057)
2015Q1	1.547***	(0.080)
2015Q2	1.497***	(0.071)
2015Q3	1.543***	(0.070)
2015Q4	1.421***	(0.063)
2016Q1	1.692***	(0.095)
2016Q2	1.666***	(0.080)
2016Q3	1.707***	(0.085)
2016Q4	1.957***	(0.144)
Decade Discount Rate δ	0.066***	(0.007)
One Tree Hill School Zone	−0.396***	(0.014)
Double Grammar Zone	0.534***	(0.036)
5 Rooms	1.043***	(0.042)
6 Rooms	1.061***	(0.042)
7 Rooms	1.274***	(0.046)
8+Rooms	1.247***	(0.047)
Flat (0-10%)	0.036	(0.026)
Steeply Sloped (25-50%)	−0.101***	(0.024)
Extremely Steeply Sloped (50-70%)	−0.342***	(0.055)
Adjusted R^2	0.940	
Log-Likelihood	-40865.385	
AIC	81830.77	
BIC	82162.8	
Number of Observations	5,657	

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimation results for the generalized builder's models using alternative slope class. Selwyn College school zone is the base school zone. 2-to-4-room category is set as the reference room group. Moderately sloped land (10-25%) is the base land slope class. Robust Standard errors in parentheses.

B.2 AIMS Address Components

To comprise full addresses for AIMS Address Component dataset, information on the component types and orders described in the table below is used. More information about AIMS Address Component data can be found at LINZ data service site.

Table B.3: AIMS: Address Component Type and Order

Address Component Type	Address Component Order
Unit Type	1
Unit Value	2
Level Type	3
Level Value	4
Building Part	5
Building Name	6
Address Number Prefix	7
Address Number	8
Address Number Suffix	9
Address Number High	10
Road Name Prefix	11
Road Name	12
Road Type Name	13
Road Suffix Name	14
Water Route Name	15
Water Body Name	16
Suburb/Locality Name	17
Town/City Name	18
Postcode	19
Suburb/Locality ID	20
RoadCenterLine	21

B.3 Building Outlines

There were quite number of mismatches between geocoded addresses and building outlines. We hand corrected as much as possible before performing spatial join and assign slopes from building outlines to addresses. Three generalized models were estimated using slopes constructed from building outlines.

In model (1), we used slopes from building outlines for the entire sample. There were 8 observations missing slopes from building outlines. 11 observations with slopes from building outlines larger than 70% (35°) were recoded to the slope class steep (48-70% or 26-35°) instead of dropped.

In model (2), we kept land parcel slopes for 5,048 properties that don't share spatial extends with others and replaced land parcel slopes with building outline slopes for 609 properties that share spatial extends with others.

In model (3), we kept land parcel slopes for 5,637 freehold properties, and replaced land parcel slopes with building outline slopes for 20 cross lease properties.

Results are presented in Table B.4 on the next page. Overall these results are consistent with the results in the main analysis. Per square meter land prices decrease with land slopes. Estimated constant quality land price indices increased by 2.76, 2.78, 2.77-fold over the 10 years in models (1) to (3) accordingly. Recall, using parcel slopes the main analysis shows land prices increased by 2.78-fold over the 10 years.

Table B.4: Estimation Results – Generalized Models with Building Outlines

	Model (1)		Model (2)		Model (3)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
2007Q1	0.680***	(0.053)	0.692***	(0.053)	0.694***	(0.054)
2007Q2	0.721***	(0.055)	0.745***	(0.052)	0.750***	(0.052)
2007Q3	0.723***	(0.068)	0.726***	(0.069)	0.729***	(0.069)
2007Q4	0.631***	(0.049)	0.640***	(0.051)	0.642***	(0.051)
2008Q1	0.675***	(0.053)	0.688***	(0.053)	0.689***	(0.053)
2008Q2	0.562***	(0.044)	0.573***	(0.042)	0.579***	(0.041)
2008Q3	0.622***	(0.088)	0.633***	(0.090)	0.632***	(0.090)
2008Q4	0.506***	(0.054)	0.515***	(0.055)	0.527***	(0.058)
2009Q1	0.439***	(0.053)	0.444***	(0.053)	0.446***	(0.053)
2009Q2	0.489***	(0.048)	0.496***	(0.047)	0.499***	(0.047)
2009Q3	0.553***	(0.042)	0.564***	(0.042)	0.569***	(0.041)
2009Q4	0.623***	(0.044)	0.631***	(0.045)	0.635***	(0.045)
2010Q1	0.575***	(0.039)	0.590***	(0.040)	0.594***	(0.041)
2010Q2	0.693***	(0.058)	0.701***	(0.057)	0.714***	(0.058)
2010Q3	0.659***	(0.061)	0.667***	(0.063)	0.671***	(0.064)
2010Q4	0.611***	(0.058)	0.622***	(0.058)	0.624***	(0.058)
2011Q1	0.542***	(0.055)	0.563***	(0.053)	0.567***	(0.053)
2011Q2	0.705***	(0.066)	0.709***	(0.065)	0.711***	(0.065)
2011Q3	0.606***	(0.070)	0.616***	(0.064)	0.619***	(0.064)
2011Q4	0.672***	(0.069)	0.683***	(0.067)	0.686***	(0.067)
2012Q1	0.667***	(0.050)	0.686***	(0.048)	0.688***	(0.049)
2012Q2	0.647***	(0.043)	0.657***	(0.043)	0.660***	(0.043)
2012Q3	0.669***	(0.044)	0.671***	(0.044)	0.682***	(0.045)
2012Q4	0.835***	(0.044)	0.845***	(0.043)	0.848***	(0.042)
2013Q1	0.779***	(0.045)	0.786***	(0.044)	0.795***	(0.044)
2013Q2	0.942***	(0.054)	0.944***	(0.054)	0.950***	(0.054)
2013Q3	0.984***	(0.059)	1.020***	(0.060)	1.025***	(0.060)
2013Q4	0.954***	(0.060)	0.972***	(0.061)	0.978***	(0.061)
2014Q1	0.953***	(0.062)	0.959***	(0.061)	0.967***	(0.061)
2014Q2	1.168***	(0.079)	1.173***	(0.080)	1.174***	(0.080)
2014Q3	1.242***	(0.080)	1.257***	(0.079)	1.260***	(0.079)
2014Q4	1.182***	(0.058)	1.214***	(0.058)	1.219***	(0.058)
2015Q1	1.481***	(0.086)	1.494***	(0.081)	1.506***	(0.082)
2015Q2	1.466***	(0.071)	1.467***	(0.073)	1.468***	(0.073)
2015Q3	1.489***	(0.067)	1.506***	(0.066)	1.522***	(0.066)
2015Q4	1.402***	(0.063)	1.419***	(0.060)	1.422***	(0.060)
2016Q1	1.638***	(0.096)	1.656***	(0.093)	1.657***	(0.093)
2016Q2	1.569***	(0.080)	1.614***	(0.077)	1.640***	(0.073)
2016Q3	1.643***	(0.093)	1.669***	(0.085)	1.668***	(0.085)
2016Q4	1.874***	(0.144)	1.922***	(0.139)	1.924***	(0.137)
Decade Discount Rate δ	0.065***	(0.007)	0.066***	(0.007)	0.067***	(0.007)
One Tree Hill School Zone	−0.379***	(0.015)	−0.395***	(0.014)	−0.396***	(0.014)
Double Grammar Zone	0.550***	(0.038)	0.536***	(0.036)	0.539***	(0.036)
5 Rooms	1.061***	(0.043)	1.040***	(0.042)	1.038***	(0.042)
6 Rooms	1.080***	(0.044)	1.058***	(0.043)	1.062***	(0.043)
7 Rooms	1.295***	(0.047)	1.262***	(0.046)	1.264***	(0.046)
8+Rooms	1.260***	(0.048)	1.240***	(0.047)	1.234***	(0.047)
Flat to gently undulating (0-3°)	0.032	(0.030)	0.069*	(0.040)	0.070*	(0.042)
Undulating (4-7°)	0.011	(0.028)	0.060**	(0.025)	0.057**	(0.025)
Strongly rolling (16-20°)	−0.094***	(0.033)	−0.059*	(0.034)	−0.041	(0.036)
Moderately steep (21-25°)	−0.168**	(0.072)	−0.128***	(0.045)	−0.169***	(0.035)
Steep (26-35°)	−0.256***	(0.054)	−0.258***	(0.048)	−0.269***	(0.044)
Adjusted R^2	0.939		0.939		0.940	
Log-Likelihood	-40828.889		-40872.808		-40855.831	
AIC	81761.78		81849.62		81815.663	
BIC	82107.02		82194.93		82160.98	
Number of Observations	5,649		5,657		5,657	

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This table presents estimation results for the generalized builder's models using slopes constructed from building outlines. Selwyn College school zone is the base school zone. 2-to-4-room category is set as the reference room group. Rolling land (8-15°) is the base land slope class. Robust Standard errors in parentheses.

Appendix C: Appendix of Chapter 3

C.1 Shopping Centers and Safe-swim Beaches in Auckland

Table C.1: Shopping Centers in Auckland

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

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

Table C.2: Beaches without Long-term Water Quality Alarm

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