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Abstract

This study examines the impact of flood hazard zone location on residential property values. The study utilises data from over 2,000 private residential property sales occurred during 2006 in North Shore City, New Zealand. A spatial autoregressive hedonic model is developed to provide efficient estimates of the marginal effect of flood prone risks on property values. Our results suggest that a property located within a flood hazard zone sells for 4.3% less than an equivalent property located outside the flood hazard zone. Given the median house price, estimated discount associated with flood risks is approximately NZ$22,000.

Keywords: Flood hazard; Spatial hedonic; Amenity value

JEL classification: Q15; Q51

1. Introduction

The least frequently occurring natural hazards include earthquakes, volcanism, tsunami, meteorological events such as storms, and fire. While of low return frequency, natural hazards are potentially of major regional significance. In the case of flooding it is possible that many properties are in a flood hazard zone but the owners' have never experienced a flood. Even though a flood hazard zone might be based on a 1% chance of occurring every year a storm causing the area to be flooded may not have occurred in the last several decades. Because of the lack of flooding experience it is likely that property owners in floodplains are not aware of the risk of living in a flood prone area. Information about natural hazards is imperfect and home owners may fail to adequately internalise the costs associated with living in that location and rely on subjective assessments about the likelihood of personal injury and property damage caused by natural risks (Beron *et al*., 1997; Troy and Romm, 2004). Consumer perception of risk is a function of personal experience with floods, the history of past flooding in the community, the level of risk that exists, and how each individual responds to risks (Holway and Burby, 1990). It has been suggested in previous research that recent experience with flooding raises perceived risk associated with flood prone areas and that people poorly integrate risks into their decisions, especially when the risk is of high consequence and low probability (Bartošová *et al.,* 1999; Zhai *et al*., 2003; Bin and Polasky, 2004; Bin and Kruse, 2006).

There appears to be a limited but growing literature on the effects of flooding risk on property values. Much of the previous research however has been carried out in the United States where major flooding events have frequently been reported and the National Flood Insurance Reform Act mandates insurance purchase. Several studies use property location vis-à-vis a flood plain and find that location in a flood plain reduces property values (Holway and Burby, 1990; Harrison *et al*., 2001; Guttery *et al*., 2004). These three studies are of further interest because they show that the negative consequences of flood zone location were more pronounced after the passage of the National Flood Insurance Reform Act in 1994. These results suggest that if the marginal purchaser is not forced to acquire hazard insurance, then the negative effect of this environmental attribute is limited by the individual's subjective assessment of the risk of loss from flooding. However, Bin and Kruse (2006) found that the National Flood Insurance program has an insignificant influence on property values in floodplains due to the fact that the current insurance program offers limited coverage. With concern over sea level rise and an increase in the frequency of adverse climate events research finds lower property prices within the flood zones in the coastal housing market. However, coastal property that is exposed to natural hazards, such as wind and flooding, often commands a premium for being ocean front. Isolating the effects of proximity to water from risk is a topic requiring further research (Bin *et al*., 2006a,b; Bin and Kruse, 2006).

The aim of this study is to estimate the impact of flood hazard zone location on residential property values from over 2,000 private residential property sales occurred during 2006 in North Shore City, New Zealand. This paper builds on the existing literature dealing with flood hazard zones by including a comprehensive range of explanatory variables into the hedonic model and by using spatial econometric analysis. In addition to controlling for location in a flood plain we use geographical information systems (GIS) data on location with respect to the coast, nearest park, nearest stream, nearest motorway access ramp, local business centre and central business district (CBD). Categorical variables are used to capture the effect of contour, quality of landscape, types and scope of views. In addition to variables describing the structural characteristics of the residential property we control for income and ethnicity. Unobserved neighborhood characteristics are controlled with local fixed effects. Although spatial econometric analysis has been used previously (for example, see Bin *et al.*, 2006a,b) this paper is, to our knowledge, the first to apply the technique to a comprehensive data set that includes structural, environmental, and socioeconomic variables in an area without any mandatory insurance purchase or recent flooding experience. Given the absence of mandatory flood insurance our data should reveal the buyer's subjective assessment about the likelihood of personal injury and property damage caused by flooding.

We find that the sale price of a residential property within a flood prone area is lower than an equivalent property outside the flood prone area. We gain more efficient estimates compared to classical regression model, by controlling for spatial correlation. The remainder of this paper is divided into five sections. Section 2 describes our econometric model, Section 3 discusses our study area and the data, Section 4 presents the empirical results of our hedonic analysis, and Section 5 closes with some concluding remarks.

2. Econometric model

This study uses hedonic price analysis to estimate the impact of flood hazard locations on the sale price of properties. Initially the following traditional hedonic price model is specified:

$$Log\ P_i = \beta_1 + \beta_2\, T_i + \beta_3\, H_i + \beta_4 N_i + \beta_5 L_i + \beta_6 E_i\ + \varepsilon \qquad (1)$$

where P_i = Residential sale price of the ith property and T_i, H_i, N_i, L_i, E_i = vectors of time trend, structural, neighbourhood, location, and environmental characteristics respectively, for ith property. The parameters to be estimated are $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ and ε is the random error term which is assumed to be iid ~ N(0,Ω). The semi-log form is consistent with Rosen (1974) and there is ample evidence to support this functional form as opposed to a simple linear functional form (Linneman, 1980; Paterson and Boyle, 2002; Kim *et al*., 2003; Bourassa *et al*., 2004). On statistical grounds the semi-log functional form corrects for heteroscedasticity between house value and the residuals (Basu and Thibodeau, 1998). We estimate heteroscedasticity corrected White standard errors to correct for potential heteroscedasticity.

Given the semi-log functional form, the marginal effect of a unit change in any untransformed continuous explanatory variable (or a change in one category of a dummy variable) on sale price can be measured by 100* [$exp\ (\beta_i)-1$] as a percentage. For log transformed explanatory variables, the estimated coefficients measure the price elasticities with respect to a given variable.

2.1 Spatial correlation

Classical linear regression models assume that observations ordered in space are independent of each other. In residential property analysis, however, we expect spatial dependency among house sale prices in close proximity. As Anselin (1988) explained, in the most general sense, spatial dependence (spatial autocorrelation) can be treated as a functional relationship between what happens at one point in space and what happens elsewhere. More specifically, house prices tend to be spatially correlated because neighbourhood properties share numerous location characteristics (Basu and Thibodeau, 1998; Dubin *et al*., 1999). Neighbourhood properties tend to be developed at the same time and thus have similar lot size, vintage and structural characteristics. Also, properties within a given vicinity may share a similar quality of public amenities and socioeconomic attributes. Thus the economics underlying the development of urban areas make the spatial dependence of these characteristics and the value of residential properties almost inevitable.

The first step in correcting for spatial dependence is to create a spatial weight matrix W that specifies the structure of potential spatial interaction. In this study we use a row standardised distance based spatial weight matrix to identify neighbours where $w_{ij} \neq 0$ when i and j are located within a 0.83km radius of distance and, $w_{ij} = 0$ otherwise. Diagonal elements of this matrix consist of zero elements. Following the empirical evidence, we start with the minimum distance of 0.83km at which all observations have at least one neighbour as a threshold and experiment by changing the distance around the threshold value.

Spatial dependence can be in two types: substantive or residual. Anselin (1988) introduced spatial autoregressive models which model cross sectional data in the form;

$$Y = \rho WY + X\beta + u \tag{2}$$

$$u = \lambda\, Wu + \varepsilon \tag{3}$$

$$\varepsilon \sim N(0,\, \Omega) \tag{4}$$

where Y is an $nx1$ vector of cross-sectional dependent variables, X is a nxk matrix of explanatory variables, W is a known nxn spatial weight matrix. The coefficient ρ measures the extent to which one observation is dependent on its neighbours and the coefficient λ measures the extent to which an error of one observation is associated with the errors of neighbouring observations. Spatial correlation in errors ($\lambda \neq 0$) may result when unobserved variables are spatially correlated (Case, 1991). When spatial association is substantial the specified model ($\rho \neq 0$ and $\lambda = 0$) is called a spatial lag model. Spatial error model is specified with $\lambda \neq 0$ and $\rho = 0$.

As Anselin (1988) explained, when the spatial association is substantial ordinary least squares (OLS) will lead the parameter estimates to be biased and inconsistent. Residual spatial correlation on the other hand leads OLS estimation to be unbiased but inefficient and may lead to incorrect inferences. For the model specified in Equation 1, we first obtain estimators using OLS and then test for spatial correlation. Then we estimate coefficients of the spatial autoregression model using maximum likelihood (ML)[1].

3. Data

Our study uses residential property sales data from New Zealand's fourth largest city, North Shore City. The city has an unbroken coastline of 140km, an area of approximately 13,000 hectares, and around 72,000 households. Home ownership is high (over 60%), the city's

[1] The estimation is implemented within the GeoDa v.0.9.5-I (beta) environment in conjunction with R for windows 2.2.1

population is mostly European and the median household income is NZ$76,000. The average land uptake has been 17 hectares per annum over the last five years with only 50 hectares remaining and the pressure that this has put on land supply in recent years has resulted in prices escalating sharply (Bayleys Research, 2007). Between 1981 and 2004 the real price of vacant residential sections increased by around 400% in North Shore (Grimes and Aitken, 2005). Coastal suburbs of Northcote, Devonport, Milford, Takapuna and the East Coast Bays provide some of the most sought after and valuable residential real estate in New Zealand and comprises 16% of the 1636 properties which have sold for in excess of $1million in New Zealand in 2006 (Bayleys Research, 2007).

Our data consist of 2, 241 transactions of individually owned free standing residential homes recorded in 2006. Figure 1 illustrates the observations on a map of North Shore City. The data used in this paper come from four different sources: the official database for all real estate transactions[2] provided information on sale price, date of sale, house structural variables, environmental variables and some neighbourhood characteristics for each transaction; the 2006 New Zealand Census of Population and Dwellings for additional neighbourhood characteristics (at the mesh block level); GIS for location characteristics; and North Shore City Council (NSCC) for flood zone information. The variables used in the hedonic price function are defined and described in Appendix A and the descriptive statistics appear in Table 1. House sale prices are adjusted for inflation to 2006 Quarter 1 prices using the quarterly house price index. The median selling price (real) for 2006 was NZ$518,056 with a minimum sale price of NZ$130,000 and a maximum of NZ$4,856,176.

[Figure 1]

[2] Property sales data were provided by Quotable Value New Zealand (QVNZ).

3.1 Structural variables

Structural characteristics included as continuous variables are: land area, building floor area and the number of garages; and, as categorical variables: the decade at which the principle structure was built, exterior materials, roofing materials, roof condition and the architectural style. Both land and floor area are in natural logarithms. It is expected that an increase in any of the continuous structural variables will lead to an increase in the property prices. The architectural style of the house and decade built are expected to be correlated as each style corresponds to a distinct period of time.

3.2 Environmental variables

Categorical variables are used to control for the environmental amenities, namely view, contour and landscape. Categorical measures of the type of the focal point of view (water or other) and the scope (slight, moderate or wide) of the view were available. A water view was defined as having a sea, lake, or harbour view. If a property has multiple view type (i.e. looks across the city or suburbs, to a lake, river or sea view) then the property was marked as having a water view. Other views were defined as city, suburban or landscape and included views of a park provided there is some depth in a built-up urban area. We combine the two variables to construct a VIEW variable with six categories (slight other view, moderate other view, wide other view, slight water view, moderate water view or wide water view).

3.3 Flood variable

Out of the 78,000 buildings in North Shore City approximately 3% are estimated to be affected by flood plains (NSCC, 2007). It is possible that many properties have always been in a flood hazard zone but have never experienced flooding problems. The NSCC is however legally obliged to make any information in their possession available to the public upon request under the Official Information Act and this is usually done by means of a Land Information Memorandum (LIM) or a Project Information Memorandum (PIM). Prior to mid-2006 only information on the presence of the flood plain was public information. Flood plain maps became available mid-2006 (NSCC, 2007). It is standard practice for buyers to obtain a LIM report which enable existing property owners and potentially new property owners to make informed decisions on buying a property in a flood prone area. Building or altering buildings or structures, or landscape within a floodplain requires Council consent. Thus both perceived risk associated with being in a flood plain zone and planning rules that limit land use *inter alia* underpin the buyer's assessment of market value.

The FLOOD dummy variable takes a value of 1 if the property is either in 100 year flood plain or in the flood sensitive area or both. We expect the location on flood hazard area will have a negative effect on the value of the property. As defined by the NSCC, floodplains are the areas of land adjacent to waterways that would be inundated with flood waters during a flood event that has a 1% chance of occurring or being exceeded in every year. These are known as the "100 year floodplain" areas. The flood sensitive areas indicate areas of uncertainty beyond the flood plains that is within 500mm in elevation of the predicted flood level. About 14% of the properties in our data are located in the flood hazard area.

3.4 Neighbourhood variables

Neighbourhood characteristics include the measures of neighbourhood income, ethnicity, and the overall quality of the immediate neighbourhood. In addition we added a series of SUBURB dummy variables for location in submarkets to control for unobserved socio economic characteristics. The submarket used here are the neighbourhoods locally known as suburbs. Suburbs are different from the census geographic units called "area units". Count data at the mesh block[3] level on the neighbourhood income, ethnic mix were available from the 2006 census. Using census data we construct two continuous variables, %HIGHINCOME and %NONEURO, where %HIGHINCOME is the percentage of households with above $50,000 mesh block income and %NONEURO is the percentage of non-European ethnics in the meshblock.

3.5 Location variables

The exact location of every observation was geocoded so that we could use GIS to compute the distance between each observation and given locations. All the distances reported in Table 1 are straight line distances measured in meters. We control for the distances to the nearest park, coast, motorway access ramp, stream or creek, the distance to Auckland's CBD, and the distance to the local business centre (Takapuna). All distances are natural log transformed to incorporate non linear relationships.

In a recent study Grimes and Liang (2007) found significant impacts of the Auckland's Metropolitan Urban Limit (MUL) on the cost of land. Given the scope of this study we included a dummy variable to measure the potential impacts of Auckland's MUL on residential property prices. We look at the top part of the MUL (see Figure 1) and define DMUL dummy variable which takes the value 1 if the observation is within 1km from the MUL or 0 otherwise. Transactions that occurred outside the MUL were excluded as only 0.4% of the transactions fell into this category.

[Table 1]

[3] The mesh block is the smallest geographic unit for which statistical data are collected and processed by Statistics New Zealand. (Statistics New Zealand, 2001)

3.6 Time trend variable

Dummy variables control for the quarter in which the property was sold. The QUARTER dummies are expected to capture trends that may be associated with seasonal variation in the market.

4. Results

4.1 Testing for Spatial dependence

First we focus on the traditional OLS model (specified in Equation 1), in order to asses the presence of spatial autocorrelation. After experimenting with different distance based weight matrices it was found that a distance cut-off of 0.58km better captured the overall spatial association in our data[4], and the analysis reported henceforth are based on the W with 0.58km distance band. Moran's I statistic shows very strong evidence of positive autocorrelation in house sale prices in 2006, denoting that observations with similar values tend to locate together (See Figure 2). Lagrange multiplier (LM) tests for spatial error dependence and spatial lag dependence were both highly significant and the robust form of LM statistics indicated preference towards a spatial error model[5]. All estimation results are reported in Table 2. We incorporate spatial dependence by means of spatial autoregressive specification. The hedonic spatial error model is specified as:

$$Log\, P_i = \beta_1 + \beta_2\, T_i + \beta_3\, H_i + \beta_4 N_i + \beta_5 L_i + \beta_6 E_i + \varepsilon \tag{5}$$

$$\varepsilon = \lambda W + u \tag{6}$$

Where λ is the spatial autoregressive coefficient, W is the defined distance based spatial weight matrix, and u is assumed to be a vector of iid errors. In a spatial error model, the price at any location is a function of the local characteristics but also of the omitted variables at neighbouring locations (Kim *et al*., 2003).

[4] The best fitting spatial weight matrix, W, is chosen by comparing the goodness fit (measured by AIC and Log likelihood) of spatial autoregressive models using different spatial weight matrices.
[5] Refer to Anselin (2005) for an explanation of the use of test statistics.

[Figure 2]

Estimation results from the OLS model[6] and the ML spatial error model are presented in Table 2. The OLS model achieves a reasonable fit with an adjusted R^2 of 0.748, however the estimated coefficients are likely to be inefficient in the presence of spatial error correlation as explained above. To avoid incorrect inferences, we base our discussion on the estimation results from the spatial error model. Results from the ML spatial error model show that spatial dependency plays an important role in the house price estimation process. The spatial autoregressive coefficient λ is highly significant, indicating spatial correlation indeed exists in our data. Moran's *I* test on spatial error model depicts no evidence of remaining spatial correlation in the model. However, because the spatial error model showed evidence of heteroscedasticity[7] our estimates are based on heteroscedasticity corrected covariances[8].

4.2 Structural variables

Estimated coefficients on LAND, BFLOOR, ROOF_CON, and GARAGE are significant and have the expected signs. Sale prices are higher, the higher the land area, building floor area, the more garages and the better the roof condition. Coefficients on LAND and BFLOOR are estimated elasticities, measuring the percentage change in sales price associated with a 1% change in land or building floor area. The sale price is 2.5% higher for properties with good roof condition. The relatively large coefficient on the building floor area variable is an indication that it may be serving as a proxy for other structural variables such as the number of bed room and bath rooms. The marginal willingness to pay for an additional garage is about NZ$10,000 (2% of a median priced property).

[6] We report the results from the OLS model for comparison purposes. (Breusch-Pagan test statistics is 202.41, p-value = 4.904e-15). Reported estimates are based on heteroscedasticity corrected White standard errors.
[7] Breusch-Pagan test statistic is 132.05 (P-value = 7.555e-06)
[8] Heteroscedasticity corrected covariances are estimated by performing GLS on the spatial error model, and the standard errors reported are based on the corrected covariances. We thank Roger Bivand for suggesting this method.

Quality bungalows and contemporary style houses are estimated to be priced higher compared to post war bungalows, however there seemed to be no significant difference between other type of architectural styles and post war bungalows. The lack of significance may well be due to the expected colinearity between the decade built and the architectural style of the house. Newer houses (built in the 1990's-2000's) are estimated to be of higher value than the houses built in the 1980's. It is likely that houses which are around 60-80 years old (built in the 1900's – 1920's) command a significant premium because of their historical attributes. Results suggest that the sale price of houses built in the 1900-1910's and 1920's are 22.9% and 17.9% higher than the price of houses built in the 1980's respectively. Houses with weatherboard and roughcast exterior walls also command a premium over houses with fibre cement exterior walls and these price differences are statistically significant. Fibre cement exterior featured houses were identified as being at risk of weather-tightness problems hence significant positive coefficients on the above mentioned exterior materials are as expected.

4.3 Environmental variables

All contour dummy variables except RISE are highly significant and have negative coefficients suggesting that houses on elevated land are discounted in the market relative to houses on level surfaces. Landscape quality was not found to impact property values. Consistent with other studies, water views are found to command a premium (for example, Benson *et al.,* 1998; Seiler *et al*., 2001 and; Bourassa *et al*., 2004). Our findings show that properties with a wide view of water sell for approximately 28% more than properties with no appreciable views, all else constant. Marginal willingness to pay for a wide water view calculated at the median property price is about NZ$145,100. Premia for a slight water view and moderate water view are estimated to be 4% and 10% respectively. Interestingly, we find no significant difference between the sale price of a property with other views and that of an otherwise similar property with no appreciable view which suggests that the price effect of visible development or roads is no different from having no appreciable views.

4.4 Flood variable

The main focus of our study is to ascertain the effect of perceived flood risk on property values. Results from our study reveal a significant negative relationship. Estimated marginal effects for the FLOOD variable suggests that location in a flood risk zone lowers property price by 4.3% compared to a property located outside the flood risk zone, *ceteris paribus*. Given the median residential property price, the marginal willingness to avoid being located within a flood hazard zone is approximately NZ$22,000. The estimated discount associated with location in the flood zone is consistent with other previous studies (for example, 7.8% in Bartošová *et al*., 1999 and Bin *et al*. 2006(b); 5.8% in Bin and Polasky, 2004; 4.2% in Troy and Romm, 2004; 11% in Bin *et al*., 2006(a); and 5-10% in Bin and Kruse, 2006). Our results are relatively lower which could be explained by the lack of recent flood experience in North Shore City and the absence of mandatory insurance purchase. That people poorly integrate the risks associated with flood prone areas, when buying a residential property, could be a further reason for a relatively lower discount.

We compare the estimated coefficients from traditional OLS model and the ML spatial error model, to emphasis the importance of incorporating spatial correlation in our model. Coefficient estimate on FLOOD variable from the OLS model indicate that the sale prices are 3.4% lower if located within flood risk zone, while the spatial error model suggests a discount of 4.3%. Even though the change in magnitude is not highly significant, our inferences are now based on more efficient estimates.

4.5 Locational variables

Estimated coefficients on the distance related locational variables have expected signs except for D_CBD and D_MW. Property prices appear to fall with distance from the local business centre, nearest coast, nearest park and nearest stream/creek. However, only the effects of distance to coast and local centre are statistically significant at the 90% level. Positive coefficient on D_MW may be capturing the annoyance factor of being close to the motorway access ramp, such as noise and air pollution. The counter intuitive sign on D_CBD could be due to the colinearity between distance to the CBD and the distance to Takapuna (correlation coefficient = 0.75)[9].

Estimated coefficients reveal that on average, 1% increase in the distance to coast and Takapuna will lead property values to fall by 7.8%, and 15% respectively, all else constant. DMUL variable measures the effect of the Auckland's MUL on property prices. Results from our model shows that properties just inside (within 1km) the MUL are valued less than the inner most properties, however this difference is not statistically significant. As explained in Grimes and Liang (2007), it is possible that in early years properties just inside the MUL to have a neighbourhood which is more rural in character and valued lower than the properties further inside but as metropolitan area has urbanised, properties just inside will no longer bear this discount. On the other hand, properties just inside the MUL have some advantages such as having easy access to the country side (Grimes and Liang, 2007) and nullify the discount of having rural neighbourhoods.

[Table 2]

[9] The impact of D_CBD was not statistically significant even with the exclusion of the variable D_TAK, however, the coefficient on D_CBD became negative in the model without D_TAK .

4.6 Neighbourhood variables

Percentage of non European population in the neighbourhood has a negative relationship with property values; however this relationship is statistically insignificant. As expected, the percentage of high income households in the neighbourhood positively impacts the property values. Estimated results reveal that a 1% increase in the high income households in the meshblock increases property values by about 8%. Marginal impact of an above average overall quality of the immediate surrounding is estimated to be approximately 3%.

Coefficients on submarket dummy variables measure the sale price differentials between each suburb and Albany. Coastal Suburbs of Devonport, Takapuna, Murrays Bay, Mairangi Bay and Browns Bay command significant premiums over Albany. Hillcrest, Birkenhead, Glenfield and Northcote, on the other hand bear significant discounts. There is no evidence of any significant sales price difference in the rest of the suburbs, compared to Albany. It is estimated that the property prices in Devonport are approximately 42% higher than that in Albany.

4.7 Time related variables

The quarter dummy variables are significant indicating that the quarter in which a property is sold had an impact on the sale price. Compared to the sale prices in first quarter, properties sold in other quarters were priced higher.

5. Conclusion

Several studies have found that location in a flood plain reduces property values (for instance, Holway and Burby, 1990; Harrison *et al*., 2001; Bin and Polasky, 2004; Guttery *et al.*, 2004; Bin *et.al*., 2006a,b; and Bin and Kruse, 2006). Most studies are based in the United States where major flooding events have been reported and the National Flood Insurance Reform Act mandates insurance purchase. This paper differs from these studies in at least three areas.

First, buyer perception of risk is based on a subjective assessment of the likelihood of personal injury and property damage caused by flooding. This assessment is based primarily on public information available to all participants in the market. Second, there is no mandatory requirement to purchase insurance. Third, previous research has noted that flood prone property is often located in coastal areas and it was not possible to identify the premia attached to location and views. Our data enabled us to control for a comprehensive range of variables, including location and view amenities that can potentially influence price.

We find evidence of strong spatial correlation in the residuals of the traditional hedonic model and incorporate residual spatial dependence by means of spatial autoregressive specification. Our results show that the sale price of a residential property situated within a flood prone area is significantly lower than a comparable property located outside. Estimated marginal effects for the FLOOD variable suggests that location in a flood risk zone lowers property price by 4.3% compared to a property located outside the flood risk zone, *ceteris paribus*. Given the median residential property price, the marginal willingness to avoid being located within a flood hazard zone is approximately NZ$22,000. While these results are consistent with the previous findings the comparatively lower magnitude of the price discount associated with flood risks could be an indication of the buyer's poor integration of flooding risks when buying a residential property.

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Appendix A. Definition of variables

Variable	Description
PRICE	House sale price adjusted to 2001 quarter1 prices
LAND	Land area of the property in hectares
BFLOOR	Sum of all living spaces in square meters
BUILT_1900-10	Dummy variable for the decade that the principle structure was built (1 if built in 1900-10, 0 otherwise)
BUILT_1920	Dummy variable for the decade that the principle structure was built (1 if built in 1920, 0 otherwise)
BUILT_1930-40	Dummy variable for the decade that the principle structure was built (1 if built in 1930-40, 0 otherwise)
BUILT_1950	Dummy variable for the decade that the principle structure was built (1 if built in 1950, 0 otherwise)
BUILT_1960	Dummy variable for the decade that the principle structure was built (1 if built in 1960, 0 otherwise)
BUILT_1970	Dummy variable for the decade that the principle structure was built (1 if built in 1970, 0 otherwise)
BUILT_1990	Dummy variable for the decade that the principle structure was built (1 if built in 1990, 0 otherwise)
BUILT_2000	Dummy variable for the decade that the principle structure was built (1 if built in 2000, 0 otherwise)
	The omitted category is "1980"
WALL_WBOARD	Dummy variable for Wall construction material (1 if Weatherboard, 0 otherwise)
WALL_BRICK	Dummy variable for Wall construction material (1 if Brick, 0 otherwise)
WALL_MIX	Dummy variable for Wall construction material (1 if Mix Material, 0 otherwise)
WALL_ROUGHCST	Dummy variable for Wall construction material (1 if Roughcst, 0 otherwise)
WALL_OTHER	Dummy variable for Wall construction material (1 if Other materials, 0 otherwise)
	The omitted category is Fibre Cement
ROOF_CON	Dummy variable for roof condition (1 if good, 0 otherwise)
ROOF_STEEL	Dummy variable for Roof construction material (1 if Steel or Galvanised Iron, 0 otherwise)
ROOF_OTHER	Dummy variable for Roof construction material (1 if Other materials, 0 otherwise)
	The omitted category is "Tile"
GARAGE	Number of formed car parks
QBANGALOW	Dummy variable for Architectural style of the house (1 if Quality Bungalow, 0 otherwise)
CONTEMPORARY	Dummy variable for Architectural style of the house (1 if Contemporary, 0 otherwise)

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Variable	Description
VILLA	Dummy variable for Architectural style of the house (1 if Villa, 0 otherwise)
PWBUNGALOW	Dummy variable for Architectural style of the house (1 if Pre-War Bungalow, 0 otherwise)
OTHERSTYLE	Dummy variable for Architectural style of the house (1 if Other styles, 0 otherwise)
	The omitted category is "Post-War Bungalow"
FALL	Dummy variable for Contour (1 if Easy/Moderate Fall, 0 otherwise)
RISE	Dummy variable for Contour (1 if Easy/Moderate Rise, 0 otherwise)
STEEP_F	Dummy variable for Contour (1 if Steep Fall, 0 otherwise)
STEEP_R	Dummy variable for Contour (1 if Steep Rise, 0 otherwise)
	The omitted category is "Level"
LANDSCAPE_G	Dummy variable for the quality of landscaping (1 if Good quality, 0 otherwise)
LANDSCAPE_P	Dummy variable for the quality of landscaping (1 if poor quality, 0 otherwise)
	The omitted category is "Average quality"
VIEW_OTHER_M	Dummy variable for a view (1 if other view of moderate scope, 0 otherwise)
VIEW_OTHER_S	Dummy variable for a view (1 if other view of slight scope, 0 otherwise)
VIEW_OTHER_W	Dummy variable for a view (1 if other view of wide scope, 0 otherwise)
VIEW_WATER_M	Dummy variable for a view (1 if water view of moderate scope, 0 otherwise)
VIEW_WATER_S	Dummy variable for a view (1 if water view of slight scope, 0 otherwise)
VIEW_WATER_W	Dummy variable for a view (1 if water view of wide scope, 0 otherwise)
	The omitted category is "no appreciable view"
FLOOD	Dummy variable for flood hazard area (1 if the house is within the flood hazard area, 0 otherwise)
%NONEURO	Percentage of non European ethnic groups in the mesh-block
%HIGHINCOME	Percentage of houses with family income above $50,000 in the mesh-block
SUBURB1	Dummy variable for a suburb (1 if Birkenhead, 0 otherwise)
SUBURB2	Dummy variable for a suburb (1 if Browns Bay, 0 otherwise)
SUBURB3	Dummy variable for a suburb (1 if Campbells Bay, 0 otherwise)
SUBURB4	Dummy variable for a suburb (1 if Castor Bay, 0 otherwise)
SUBURB5	Dummy variable for a suburb (1 if Devonport, 0 otherwise)
SUBURB6	Dummy variable for a suburb (1 if East Coast Bays, 0 otherwise)
SUBURB7	Dummy variable for a suburb (1 if Forrest Hill, 0 otherwise)

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(*continued*)

Variable	Description
SUBURB8	Dummy variable for a suburb (1 if Glenfield, 0 otherwise)
SUBURB9	Dummy variable for a suburb (1 if Greenhithe, 0 otherwise)
SUBURB10	Dummy variable for a suburb (1 if Hillcrest, 0 otherwise)
SUBURB11	Dummy variable for a suburb (1 if Mairangi Bay, 0 otherwise)
SUBURB12	Dummy variable for a suburb (1 if Milford, 0 otherwise)
SUBURB13	Dummy variable for a suburb (1 if Murrays Bay, 0 otherwise)
SUBURB14	Dummy variable for a suburb (1 if Northcote, 0 otherwise)
SUBURB15	Dummy variable for a suburb (1 if Rothesay Bay, 0 otherwise)
SUBURB16	Dummy variable for a suburb (1 if Sunnynook, 0 otherwise)
SUBURB17	Dummy variable for a suburb (1 if Takapuna, 0 otherwise)
SUBURB18	Dummy variable for a suburb (1 if Torbay, 0 otherwise)
SUBURB19	Dummy variable for a suburb (1 if Waiake, 0 otherwise)
	The omitted category is "Albany"
CSI	Dummy variable for overall quality of the immediate surrounding (1 if Average and below, 0 otherwise)
D_CBD	Distance to Auckland's Central Business District in meters
D_PARK	Distance to the nearest park in meters
D_COAST	Distance to the nearest coast in meters
D_STREAM	Distance to the nearest creek or stream in meters
D_MW	Distance to the nearest Motorway Ramp in meters
D_TAKAPUNA	Distance to the Local Business Centre, Takapuna in meters
DMUL	Dummy variable for Metropolitan Urban Limit (1 if the house is within 1km from the top part of the MUL, 0 otherwise)
QUARTER2	Dummy variable for the quarter that the house was sold (1 if 2nd Quarter, 0 otherwise)
QUARTER3	Dummy variable for the quarter that the house was sold (1 if 3rd Quarter, 0 otherwise)
QUARTER4	Dummy variable for the quarter that the house was sold (1 if 4th Quarter, 0 otherwise)
	The omitted category is "1st Quarter"

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Figures

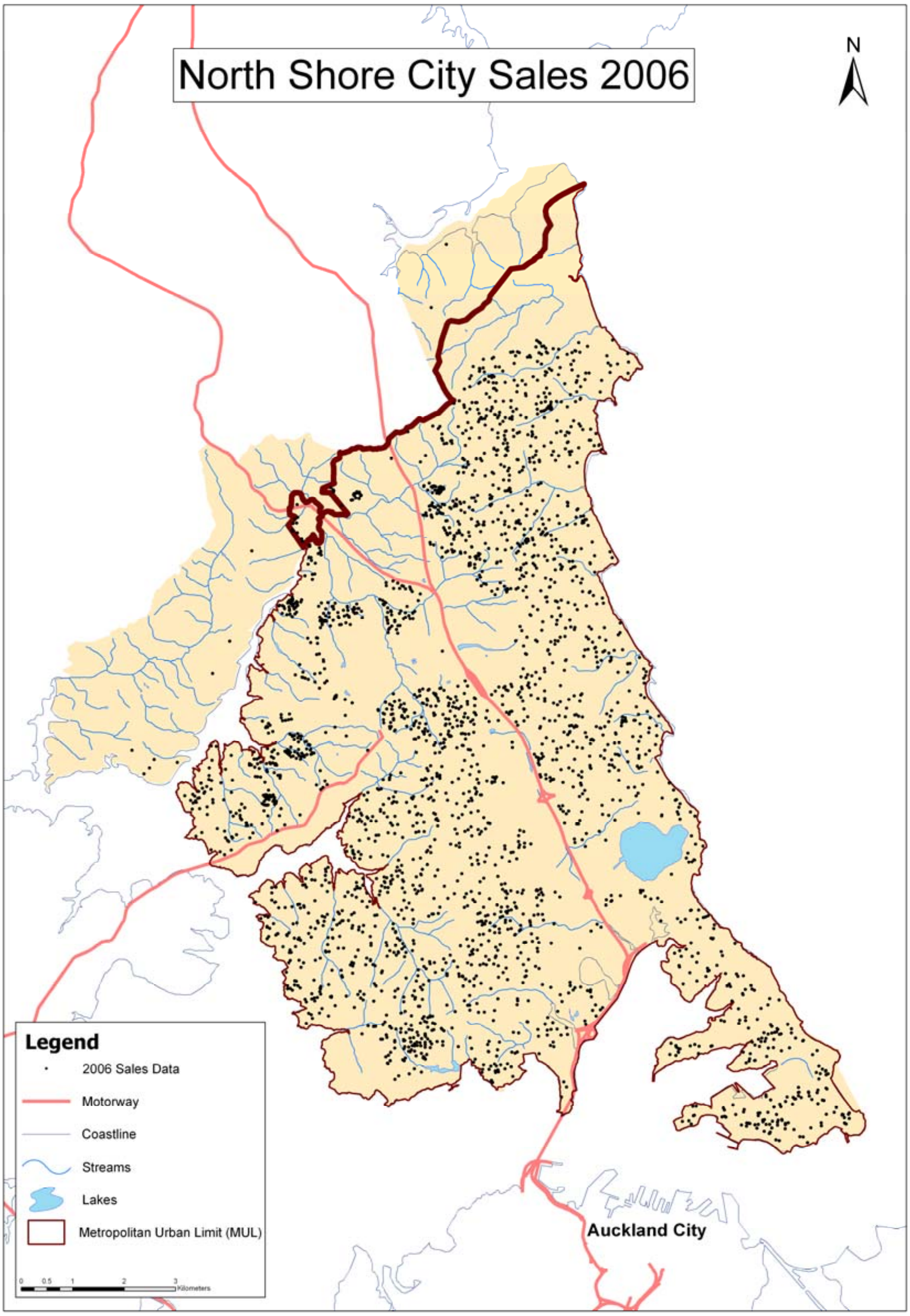

Figure 1. Locations of sale transactions. Note: figure is based on 2,251 residential transactions occurred during 2006 in North Shore City, we have not included the 10 properties that lie outside the MUL in our estimation.

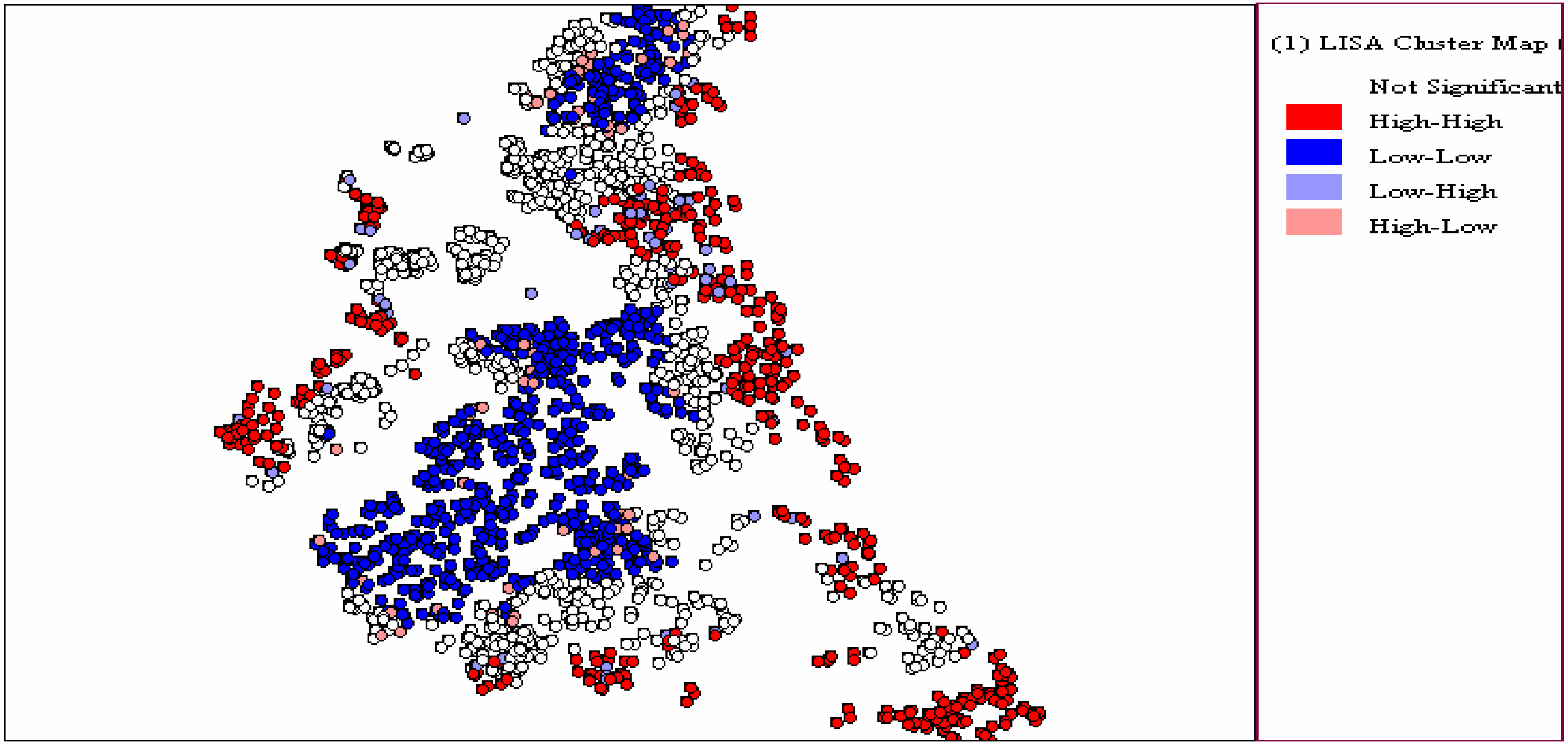

Figure 2. Local Indication of Spatial Association (LISA) cluster map. Note: figure is based on 2,241 residential transactions occurred during 2006 in North Shore City. Red dots are residential properties whose prices are high and are situated close to high priced properties. Dark blue dots are houses whose prices are low and are situated close to low priced houses. Pink and light blue dots represent spatial outliers (high priced close to low priced and vice versa).

Tables

Table 1

Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
PRICE	581840.037	319848.775	130000.000	4856175.602
LAND	0.075	0.031	0.018	0.504
BFLOOR	182.400	70.803	40.000	770.000
BUILT_1900-10	0.033		0.000	1.000
BUILT_1920	0.026		0.000	1.000
BUILT_1930-40	0.023		0.000	1.000
BUILT_1950	0.053		0.000	1.000
BUILT_1960	0.155		0.000	1.000
BUILT_1970	0.216		0.000	1.000
BUILT_1990	0.168		0.000	1.000
BUILT_2000	0.211		0.000	1.000
WALL_WBOARD	0.398		0.000	1.000
WALL_BRICK	0.135		0.000	1.000
WALL_MIX	0.167		0.000	1.000
WALL_ROUGHCST	0.168		0.000	1.000
WALL_OTHER	0.020		0.000	1.000
ROOF_STEEL	0.355		0.000	1.000
ROOF_OTHER	0.031		0.000	1.000
ROOF_CON	0.707		0.000	1.000
GARAGE	1.627	0.709	0.000	6.000
QBUNGALOW	0.251		0.000	1.000
CONTEMPORARY	0.045		0.000	1.000
VILLA	0.034		0.000	1.000
PWBUNGALOW	0.033		0.000	1.000
OTHERSTYLE	0.022		0.000	1.000
FALL	0.323		0.000	1.000
RISE	0.262		0.000	1.000
STEEP_F	0.060		0.000	1.000
STEEP_R	0.041		0.000	1.000
LANDSCAPE_G	0.184		0.000	1.000
LANDSCAPE_P	0.054		0.000	1.000
VIEW_OTHER_M	0.174		0.000	1.000
VIEW_OTHER_S	0.275		0.000	1.000
VIEW_OTHER_W	0.018		0.000	1.000
VIEW_WATER_M	0.088		0.000	1.000
VIEW_WATER_S	0.083		0.000	1.000

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Table 1(continued)

Variable	Mean	Std. Dev.	Minimum	Maximum
VIEW_WATER_W	0.027		0.000	1.000
FLOOD	0.145		0.000	1.000
%NONEURO	0.338	0.148	0.040	0.850
%HIGHINCOME	0.624	0.123	0.000	1.000
SUBURB1	0.158		0.000	1.000
SUBURB2	0.057		0.000	1.000
SUBURB3	0.005		0.000	1.000
SUBURB4	0.013		0.000	1.000
SUBURB5	0.050		0.000	1.000
SUBURB6	0.031		0.000	1.000
SUBURB7	0.034		0.000	1.000
SUBURB8	0.141		0.000	1.000
SUBURB9	0.049		0.000	1.000
SUBURB10	0.004		0.000	1.000
SUBURB11	0.019		0.000	1.000
SUBURB12	0.021		0.000	1.000
SUBURB13	0.014		0.000	1.000
SUBURB14	0.044		0.000	1.000
SUBURB15	0.010		0.000	1.000
SUBURB16	0.019		0.000	1.000
SUBURB17	0.032		0.000	1.000
SUBURB18	0.068		0.000	1.000
SUBURB19	0.005		0.000	1.000
CSI	0.687		0.000	1.000
D_CBD	9969.000	3657.486	1771.000	16974.000
D_PARK	765.510	468.873	49.080	3028.560
D_COAST	1189.170	817.951	14.790	3300.510
D_STREAM	346.162	350.602	0.354	2304.910
D_MW	2481.400	1388.084	161.000	6087.400
D_TAKAPUNA	6049.218	2225.811	559.315	10579.157
DMUL	0.049		0.000	1.000
QUARTER2	0.285		0.000	1.000
QUARTER3	0.248		0.000	1.000
QUARTER4	0.232		0.000	1.000

Note: table is based on estimation sample of 2,241 residential property transactions occurred in North Shore City, during 2006.Summary statistics are given for variables prior to logarithmic transformation. See Appendix A for variable descriptions. The mean value for a dummy variable indicates the proportion of sales with the particular attribute.

Table 2
Estimation Results

	Traditional OLS Model			Spatial Error Model		
Variable	Coefficient		Std. Error	Coefficient		Std. Error
(INTERCEPT)	14.5813	***	0.4014	13.4869	***	0.5322
LOG(LAND)	0.2385	***	0.0185	0.2329	***	0.0162
LOG(BFLOOR)	0.3516	***	0.0180	0.2984	***	0.0170
BUILT_1900-10	0.2680	***	0.0779	0.2066	***	0.0654
BUILT_1920	0.1879	***	0.0659	0.1648	***	0.0593
BUILT_1930-40	0.0530		0.0431	0.0396		0.0376
BUILT_1950	0.0032		0.0250	0.0139		0.0213
BUILT_1960	-0.0271	*	0.0162	0.0008		0.0144
BUILT_1970	-0.0455	***	0.0131	-0.0192		0.0118
BUILT_1990	0.0467	***	0.0171	0.0657	***	0.0149
BUILT_2000	0.1159	***	0.0217	0.1422	***	0.0200
WALL_WBOARD	0.0333	***	0.0129	0.0208	*	0.0116
WALL_BRICK	-0.0085		0.0181	-0.0101		0.0161
WALL_MIX	0.0340	*	0.0178	0.0256		0.0157
WALL_ROUGHCST	0.0535	**	0.0209	0.0352	*	0.0183
WALL_OTHER	0.0218		0.0261	-0.0191		0.0233
ROOF_STEEL	-0.0164	*	0.0093	-0.0083		0.0079
ROOF_OTHER	0.0293		0.0315	0.0194		0.0252
ROOF_CON	0.0047		0.0105	0.0246	***	0.0094
GARAGE	0.0268	***	0.0075	0.0199	***	0.0064
OBUNGALOW	0.0271	**	0.0120	0.0324	***	0.0102
CONTEMPORARY	0.0659	**	0.0260	0.0440	**	0.0220
VILLA	0.0788		0.0717	0.0367		0.0618
PWBUNGALOW	0.0497		0.0558	0.0065		0.0521
OTHERSTYLE	0.0586	**	0.0268	0.0345		0.0240
FALL	-0.0223	*	0.0115	-0.0288	***	0.0098
RISE	-0.0173		0.0113	-0.0101		0.0100
STEEP_F	-0.0736	***	0.0180	-0.0606	***	0.0148
STEEP_R	-0.0679	***	0.0193	-0.0538	***	0.0161
LANDSCAPE_G	0.0150		0.0098	0.0089		0.0081
LANDSCAPE_P	-0.0134		0.0157	0.0004		0.0124
VIEW_OTHER_M	-0.0147		0.0112	-0.0015		0.0101
VIEW_OTHER_S	0.0029		0.0100	0.0078		0.0090
VIEW_OTHER_W	-0.0004		0.0301	0.0147		0.0257
VIEW_WATER_M	0.0968	***	0.0166	0.0931	***	0.0143
VIEW_WATER_S	0.0393	**	0.0184	0.0393	**	0.0162
VIEW_WATER_W	0.3009	***	0.0572	0.2457	***	0.0470
FLOOD	-0.0348	***	0.0110	-0.0434	***	0.0097
%NONEURO	-0.1141	***	0.0419	-0.0172		0.0402
%HIGHINCOME	0.1365	***	0.0446	0.0735	*	0.0380
CSI	-0.0590	***	0.0114	-0.0298	***	0.0099
LOG(D_CBD)	-0.0393		0.0414	0.0383		0.0755
LOG(D_PARK)	-0.0242	***	0.0094	-0.0078		0.0108
LOG(D_COAST)	-0.0711	***	0.0079	-0.0776	***	0.0139
LOG(D_STREAM)	-0.0007		0.0048	-0.0009		0.0047

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Table 2 (*continued*)

	Traditional OLS Model			Spatial Error Model		
Variable	Coefficient		Std. Error	Coefficient		Std. Error
LOG(D_MW)	-0.0319	***	0.0113	0.0224		0.0190
LOG(D_TAKAPUNA)	-0.1654	***	0.0321	-0.1527	**	0.0624
DMUL	-0.0061		0.0261	-0.0227		0.0465
SUBURB1	-0.1253	***	0.0306	-0.0995	**	0.0450
SUBURB2	0.0459	**	0.0207	0.0607	*	0.0365
SUBURB3	0.1781	**	0.0785	0.0869		0.0981
SUBURB4	0.0936	*	0.0480	0.1266		0.0866
SUBURB5	0.1989	***	0.0547	0.3492	***	0.0951
SUBURB6	0.0210		0.0350	0.0343		0.0459
SUBURB7	-0.0963	***	0.0273	-0.0012		0.0459
SUBURB8	-0.1793	***	0.0260	-0.0926	***	0.0307
SUBURB9	-0.1086	***	0.0363	-0.0494		0.0618
SUBURB10	-0.2741	***	0.0726	-0.1796	***	0.0642
SUBURB11	0.0835	**	0.0341	0.1304	**	0.0529
SUBURB12	0.0512		0.0491	0.0832		0.0643
SUBURB13	0.1376	***	0.0417	0.1744	***	0.0616
SUBURB14	-0.2047	***	0.0396	-0.0768	*	0.0454
SUBURB15	0.0929	***	0.0358	0.0880		0.0555
SUBURB16	-0.0480	**	0.0242	-0.0481		0.0358
SUBURB17	-0.0013		0.0544	0.2147	***	0.0769
SUBURB18	0.0740	**	0.0310	0.0442		0.0512
SUBURB19	0.1147	**	0.0456	0.0323		0.0455
QUARTER2	0.0216		0.0124	0.0252	**	0.0108
QUARTER3	0.0352		0.0119	0.0321	***	0.0105
QUARTER4	0.0309		0.0123	0.0269	***	0.0104
λ	n/a			0.77755	***	
ADJUSTED R^2	0.7482			n/a		
LOG LIKELIHOOD				795.2479		
AIC	-1105.6			-1446.5		
LM ERROR	534.9769	***		n/a		
LM LAG	60.7347	***		n/a		
RLM ERROR	496.7155	***		n/a		
RLM LAG	22.4734	***		n/a		
MORAN'S I STATISTIC	0.5631	***		-0.0090		

Note: results are based on data for 2,241 transactions of individually owned free standing residential homes recorded in 2006.Dependent variable is the natural log of sale prices. Standard errors are based on heteroscedasticity corrected covariance matrices. See Appendix A and Tables 1 for variable definitions and descriptive statistics, respectively. * Significant at the 90% confidence level, ** significant at the 95% confidence level, *** significant at the 99% confidence level