Impact of proximity to Bus Rapid Transit on nearby property values in Auckland

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Abstract

Dubbed 'The City of Cars', congestion is a prominent issue in Auckland. Auckland's first Bus Rapid Transit (BRT) system - the Northern Busway - was implemented in 2008. The 6.2 km busway network services the North Shore suburbs and provides a link to the CBD. This research aims to assess the impact of the Northern Busway on nearby residential property values. Spatial modelling is used to examine the accessibility impacts of the BRT. Namely, we use a spatial autoregressive error term (SARAR) hedonic model under difference – in – differences (DiD) framework to estimate the impact of Northern Busway on nearby property values. We employ a generalised spatial two-stage least squares (GS2SLS) estimation procedure to estimate the coefficients because it is able to produce consistent estimates even when the disturbances are heteroskedastic, as found in our data. We have observed two main findings. Firstly, the average net sale price for properties within 2 km radius catchment area (i.e. treatment group) on the North Shore increases by approximately 4% as a result of the opening of the Northern Busway (from before to after). Secondly, the price gap between the treatment group and the control group has also been shrinking thanks to the opening of the Northern Busway. Specifically, before the opening of the Northern Busway, the average net sale prices of the properties within 2 km radius catchment area is almost 6% lower compared to the rest of properties sold on the North Shore (i.e. control group). After the opening of the Northern Busway, the average net sale price for all sold properties within 2 km radius catchment area is only 2% lower compared to the rest of properties sold on the North Shore.

1. Introduction

Public transport seeks the mobility of citizens within the municipal area, and this service represents a substantial component of the quality of life that is offered to urban residents. By world standards, Auckland, the largest and most populous city in New Zealand, is characterised by low density and extremely low public transport use. As such, population density within Auckland's urbanised area is 2,492 people per km^2 (Frederikson, 2014). In contrast, Barcelona – the most densely populated European city – on average has 16,000 inhabitants per km^2. The low-density feature, coupled with high automobile-dependency, is placing enormous barriers on the operating atmosphere for public transport in Auckland.

The development of a motorway system and lack of investment in public transport, made private cars the preferred mode of transport for urban dwellers in Auckland. While in the 1950's 58% of motorised trips were by public transport this declined sharply to 2% by 2000 (Coleman, 2010). Ongoing rapid population growth and worsening traffic congestion, resulted in a substantial increase in transport investment over the last two decades, including expansion of the public transport network of rail and busways (Auckland Council, 2018).

Provision of transport infrastructure is among most costly public expenditure projects. Most recently, Auckland's City Rail Link – underground rail line expansion – is estimated to cost NZD 3.4 billion. Arguably, the heavy costs are counterbalanced by potential private and public benefits and economic growth. It is well-documented that housing prices near the public transport routes capture the external benefits of public infrastructure (for a summary see Bartholomew and Ewing, 2011) as increased accessibility can reduce travel costs to employments and activity centres. Clearly, from a policy point of view there is interest in examining property values uplift following a new transport investment to establish if the increase is sufficient to contribute the infrastructure cost recovery.

A well-designed public transport network with a high level of accessibility can deliver broad economic and social benefits to communities, including travel time and fuel consumption savings with reduced traffic congestion, plus a growth in trading opportunities. Bus Rapid Transit (BRT) is a bus-based public transport network designed to improve capacity and reliability relative to a conventional bus system, operating on bus lanes or dedicated infrastructure. The Northern Busway has been one of Auckland's major public transport success stories. With its construction starting in 2004 and opening to public in February 2008 is New Zealand's first purpose built road dedicated to public transport. The Busway connects the northern suburbs with the CBD in less than 30 minutes during peak times while it can take up to 60 minutes to commute by car. To gain comprehensive understanding of the impact of BRT on property values, in particular in a car-dependent city, we draw on the Northern Busway as a case study. We hypothesise that the improved accessibility due to the busway result in higher property values within its catchment area.

The rest of the paper is structured as follows. Section 2 summaries the literature context with respect to studies measuring accessibility and land values, transit impacts and property value impacts of BRT in Australia. Section 3 describes the case study in Auckland, followed by a discussion of the methodology adopted in section 4. Section 5 describes the data and variables used in this analysis. Section 6 presents the empirical results from the SARAR-DiD analysis. The final section concludes with an emphasis on policy implications of the findings.

2. Literature Review

House prices reflect location preferences of households. Willingness to pay for various attributes (e.g. schools, parks, employment) has been captured in numerous hedonic price studies (for a summary see Sirmans *et al*., 2005). A substantial body of research addresses the effects of accessibility to public transport on property values. Bid-rent theory helps explain the impact of accessibility on land values where land prices decrease with increasing distance to the CBD reflecting accessibility gradients with higher values reflecting higher accessibility to services (Alonso, 1964; Muth, 1969). Therefore, locations with better accessibility will have higher value and where transport infrastructure improves accessibility, it can be expected the land values will rise in those locations. As a trade-off people are willing to pay higher accommodation costs to lower their costs of commute to centres of economic activities.

Most of the previous research examining property value uplift in proximity to public transit considers rail transit modes. Duncan (2011) provides a summary of 50 such studies. Although conclusions are mixed due to differences in methods and context, majority find a property value uplift near rail transit. Based on North American studies, premiums for detached dwellings vary between 0-10% (Landis *et al*., 1995; Debrezion *et al*., 2007; Hess and Almeida, 2007). In contrast, relative novelty of BRT has not generated extensive body of literature. Original BRT studies focused on developing countries: Bogota, Columbia (Rodriguez and Targa, 2004; Munoz-Raskin, 2007) and Seoul, South Korea (Cervero and Kang, 2011; Jun, 2011). Due to lack of transaction prices, asking prices (Rodriguez and Targa 2004; Munoz-Raskin 2007) and assessed values (Cervero and Kang, 2011) were used as proxies. In both locations, the researchers observed positive value uplift. In Beijing, China, Deng and Nelson (2010) found that apartments adjacent to a BRT appreciated faster than apartments not served by the BRT. While Ma *et al*. (2013) finds no significant price premiums for properties located near BRT station areas. Differences in attributes of BRT and rail transit such as capacity, frequency and comfort are potentially contributing to the non-significant effects of proximity to BRT stations. Likewise, value uplift was negligible in a number of Australian studies. Mulley (2014) and Mulley and Tsai (2016) examined a BRT in Sydney. In Mulley (2014) property values increased 0.7% which was overshadowed by a 9.2% decline for houses within 100 metres of the stations which is effect of their negative externalities (e.g. noise, congestion around stations). Mulley and Tsai (2016) observed that upon opening house prices increased by 11% but within two years the impact dissipated. In Brisbane, Mulley *et al*. (2016) detected 0.36 increase in house prices for every 250 metres closer to the BRT station. Both cities exhibit characteristics similar to the present case study of Auckland's Northern Busway – they have high car dependency, low population density and affordable car ownership. These factors result in undervaluation of BRT benefits in contrast to locations where dependence on public transport is high.

As shown above, empirical studies on the BRTs are rather limited and results are mixed. Level of economic development, characteristics of cities (e.g. density, spatial patterns etc), range of BRT services and facilities contribute to the mixed results observed in the literature. Yet, from the policy point of view, there is significant interest how to 'equitably' finance and recover significant transport infrastructure expenditures. Understanding how property market values the new transport projects serves as an effective way in equity considerations. This study aims to provide another unique context to examine the effects of bus-based infrastructure using the Northern Busway located in Auckland, New Zealand as a case study.

3. Case Study: the Northern Busway

The Northern Busway is a segregated busway that runs along the Northern Motorway (SH1) between the North Shore and Auckland CBD. The 6.2 km busway network services the North Shore suburbs and provides a link to the CBD. It is New Zealand's first BRT and it was officially opened in 2008. Originally, five dedicated stations, some with park-and-ride facilities.

Fig. 1 Northern Busway Network

Patronage has been growing 15-20% annually. Average percentage of commuters using public transport to travel to work in the vicinity:

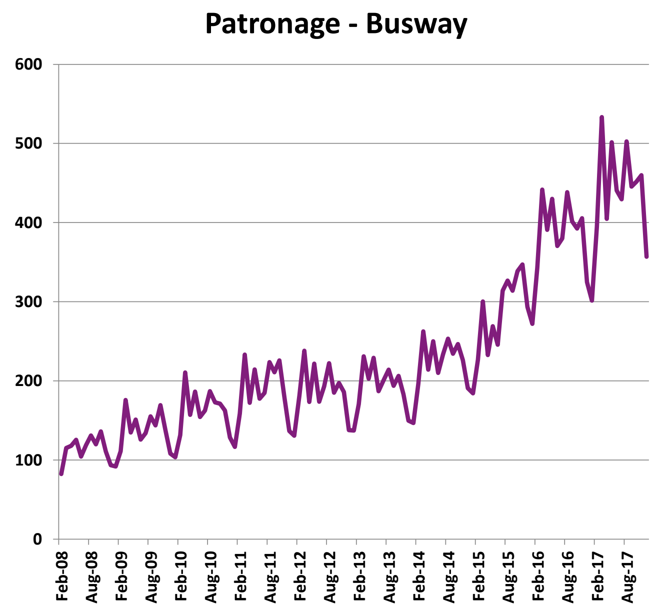

Fig. 2 Patronage from Northern Busway from Feb 2008 to August 2017

4. Model Specifications

4.1 Hedonic model

We employ the hedonic pricing model (Rosen, 1974) to understand how proximity to BRT system, an infrastructure amenity, affects property values. This approach enables us to explicitly model the sale price of a complex real estate good as a function of its various attributes including both intrinsic (i.e. physical) and extrinsic (i.e. environmental) characteristics, and that coefficients related to one specific characteristic represent its implicit (hedonic) price (Boyle and Kiel, 2001; Des Rosiers *et al*., 2010; Dubé *et al*., 2014). The estimated implicit mean price of the attributes evokes a household's willingness to pay (WTP) for a marginal increase in the individual property attributes, or the marginal willingness to pay (MWTP), for each attribute, assuming the housing market is in equilibrium (Andersson *et al*., 2015), therefore, the hedonic pricing model has been considered an effective tool for capturing the MWTP for changes in extrinsic characteristics. The general formulation of the hedonic equation to be estimated can be expressed as follows:

$$P = f(S, E, B, YQ) \tag{1}$$

where P, the net sale price of a residential property, is a function of S (the physical or structural characteristics of property), E (the environmental attributes, such as neighbourhood and locational characteristics for property), B (the infrastructure amenity variable of interest), YQ (year and quarter dummies to control for overall trends and seasonal fluctuations that may affect all of the properties).

4.2 Spatially lagged and autoregressive disturbance model (SARAR)

A key econometric drawback of Eq. (1) concerns the potential spatial dependence of the observations. Hedonic pricing model is based on ordinary least squares (OLS) method, which is unadjusted for spatial effects. In other word, the basic hedonic pricing model lacks the ability to comprise the multidimensional features shared by neighbouring properties, which may affect property values. For instance, common unobserved location characteristics, similar structural features due to contemporaneous construction, social network effects, as well as other causes of spatial dependence (Atreya *et al*., 2013). Therefore, the spatial dependence effect needs to be effectively controlled for; otherwise, it could result in inefficient, inconsistent or biased parameter estimates (Anselin and Bera, 1998; LeSage and Pace, 2009; Koschinsky *et al*., 2012).

Following prior studies (Anselin and Florax, 1995; Atreya *et al*., 2013; Diao, 2015), this paper considers two types of spatial autocorrelation. The first is under the assumption that the value of a property is influenced by the features of neighbouring houses. This type of spatial autocorrelation can be corrected by adding a spatially lagged dependent variable to Eq. (1). The second is under the assumption that the property attributes captured by the model have only local effects; however, the unobserved factors that are missing from the model specification are spatially correlated. This type of spatial autocorrelation can be solved by adding a spatially lagged error term to the regression. Let n denote the number of property transactions and k indicate the number of independent variables. A general, unconstrained spatial model, namely, the spatial autoregressive error term (SARAR), which allows for both a spatial lag and spatially correlated errors, is of the form:

$$P = \lambda W_1 P + \beta X + \varepsilon \tag{2}$$

$$\varepsilon = \rho W_2 \varepsilon + \mu$$

where P is an *n x 1* vector of residential property prices, W_1 and W_2 are the *n x n* spatial weights matrices corresponding to the spatial lag process and spatial error process, respectively, β is a *n x 1* vector of estimated coefficients, X is an *n x k* vector of explanatory variables comprises of $S, E, B,$ and YQ, λ is the spatial lag parameter, ρ is the spatial error operator, and μ is a vector of independent and identically distributed (*i.i.d*) random error terms, which is assumed to be uncorrelated to ε. $W_1 P$ is the spatially lagged dependent variable which has the ability to account for various spatially related dependencies. Following most of previous studies (Fingleton, 2008; Fingleton and Le Gallo, 2008, Kissling and Carl, 2008, Kelejian and Prucha, 2010 and Atreys *et al*., 2013), the two weights matrices W_1 and W_2, are assumed to be equal.

To test the presence of spatial dependence and estimate the above SARAR model requires the specification of the spatial weights matrix. To ensure our estimates are robust to the choice of different weighting matrix, this study suggests three different geographically derived weights based on proximities: (1) a first order contiguity matrix (**C**), where adjacent properties assigned a weight of one and zero otherwise; (2) six nearest neighbours (**6NN**), where $w_{ij} = \frac{1}{6}$ for the six nearest neighbours of a given property, and zero otherwise; and (3) eight nearest neighbours (**8NN**), where $w_{ij} = \frac{1}{8}$ for the six nearest neighbours of a given property, and zero otherwise. MATLAB was used to create these spatial weights matrices and finds the nearest neighbours for each observation by identifying those with the smallest Euclidean distance.[1] Additionally, the spatial weights matrix is row-standardised so the sum of the weights in each row equals one. This feature facilitates the interpretation of the spatial weights as the average of neighbouring values.

4.3 The SARAR-DiD model

To evaluate the impact of changing infrastructure amenities over time, while controlling for other spatial amenities that stay constant over time, the Difference-in-Differences (DiD) approach should be adapted as an efficient spatiotemporal framework (Dubé *et al*, 2014). Card (1990), Card and Krueger (1994) and Meyer *et al*. (1995) argue that the dependent variable in this case is regarded as the outcome of a quasi-experiment, because the changes in the spatial amenity (i.e. implementation of the BRT system) is a public decision by government, are exogenous to both economic agents, buyers and sellers, of the real estate market. The DiD approach has a distinct feature: it allows comparing the impact of an exogenous change of infrastructure amenity on the dependent variable (i.e. property price) by contrasting the difference in the level of this variable before and after a specific critical date (i.e. t*), between two groups, a treatment and control group. The former experiences a change of the infrastructure amenity, as opposed to the latter, which does not involve any alteration (Dubé *et al*., 2014). Thus, to determine the effect of the implementation of the BRT system in 2008 on nearby property values, three Before-After indicators: $Time_{it}$,$Treated_{it}$ and $Time_{it} * Treated_{it}$, respectively, are used to capture variable B in Eq. (1). These dummy variables are of our major interests. The dependent variable is the natural logarithm of the net sale price. A log-linear specification allows the marginal effect of each explanatory variable to vary with the level of the dependent variable. Therefore, the marginal effects of explanatory variables change as house price varies (Mueller and Loomis, 2008). By controlling for neighbourhood and

[1] The MATLAB code used for generating the spatial weights matrices and the spatial model in this study is found in the *Spatial Econometrics Toolbox* by James LeSage. The toolbox and associated documents are retrieved from: http://www.spatial-econometrics.com.

locational characteristics, and housing structure, a hedonic DiD framework is constructed as the following:

$$\ln(P_{it}) = \beta_0 + \lambda\, W_1 \ln(P_{it}) + \beta_1 S_{it} + \beta_2 E_i + \beta_3 YQ_i + \beta_4 Time_{it} + \beta_5 Treated_{it} + \beta_6 Time * Treated_{it} + \varepsilon_{it} \quad (3)$$

$$\text{and } \varepsilon_{it} = \rho W_2 \varepsilon_{it} + \mu$$

where observations i = (1,2,….n) are observed in two time periods, $Time \in \{0,1\}$, and are grouped via $Treated \in \{0,1\}$ such that $Treated_i$= 0 indicates the control group, $Treated_i$= 1 indicates the treatment group, and $Time * Treated_{it}$ represents the, the Before-After variable of an infrastructure amenity. Consequently, β_4 is the expected mean change in P_{it} from before to after the opening of the BRT system; β_5 indicates the estimated mean difference in P_{it} between the treatment and control groups prior to the opening of the BRT system; β_6 is the estimator for DiD variable: a positive value of β_6 implies that the opening of the BRT system is having a positive effect on P_{it}, similarly, a negative value indicates that the opening of the BRT system is having a negative effect on P_{it}.

The existence of spatial autocorrelation increases the possibility that the errors will not be distributed normally (Atreya *et al.*, 2013). Based on the skewness and kurtosis test, we rejected the null hypothesis of normality at 1% significance level, indicating that the error term in the OLS regression violates normal distribution assumption. Maximum likelihood (ML) estimation procedures, depend on the assumption of normality of the regression error term, while the generalised method of moments (GMM) approach does not. Thus, we employ a generalised spatial two-stage least squares (GS2SLS) estimator that produces consistent estimates. Arraiz *et al*. (2010) claim that the GS2SLS estimator is superior to the ML estimator as the former produces consistent estimates even when the disturbances are heteroskedastic, as is found in our data[2]; while the later could lead to inconsistent estimates with heteroskedasticity in place.

5. Data and Variables

5.1 Data

[2] The White's test for homoskedasticity delivered the same result, where the test value of 2424.51, we rejected the null hypothesis of homoskedasticity. Likewise, The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity (1184.89) rejected the null hypothesis of constant variance.

Several datasets from various sources were obtained and merged to form our database for analysis. Residential sales information including sale date, sale price, address, physical characteristics (interior condition, water views, type of exterior cladding) were sourced from the Auckland Council sales audit file. Population density was calculated at meshblock level using Census information obtained from Statistics NZ while deprivations index uses 9 attributes from the 2013 Census to identify the most and least socioeconomically deprived areas in New Zealand (the index is maintained by the University of Otago). Proximity to CBD and State Highway I were calculated for each property using Euclidian distance within GIS. Each observation is a single-family detached dwelling located in North Shore, Auckland and all properties in the database sold at least once between 2003 and 2015.

After eliminating properties for which data were missing, or that were not single-family residential dwellings, or no recorded geocodes, 46,779 property transactions were available for sampling. We used Stata to draw a 10% random sample. Our final data consists of 4,674 sale transactions, with the sample period (2003–2015) covers 6 years before (2003-2008) and 7 years after (2009-2015) the opening of the Northern Busway in early 2008.

5.2 Variables

The choice of included explanatory variables was mainly inspired by prior studies, availability of data and correlations of data. The explanatory variables can be further grouped into four categories:

1. S_{it} is the structural characteristics of a property, including:

- *LandArea* represents the total effective site area of the property, in square metres;
- *FloorArea* represents the total building floor area of the property, in square metres;
- *Garage* equal to one if garage present, zero otherwise;
- *Pool* equal to one if pool present, zero otherwise;
- *Crosslease* equal to one if the title of the property is a cross lease, zero otherwise (a cross lease property is one where multiple people own an undivided share in a piece of land in contrast to freehold/fee simple estate);
- *InteriorGood* equal to one if the interior of the property is rated good, zero otherwise;
- *InteriorPoor* equal to one if the interior of the property is rated poor, zero otherwise;

- *Monoclad* equal to one if the exterior appearance of the property is monolithic plaster cladding , zero otherwise;
- *WVwide* equal to one if the property has wide waterview, zero otherwise;
- *WVmoderate* equal to one if the property has moderate waterview, zero otherwise;
- *WVsignificant* equal to one if the property has significant waterview, zero otherwise;
- *Steep* equal to one if the property's contour is not levelled; zero otherwise; and
- *v1910* equal to one if the property was built in 1910 decade, zero otherwise; same for *v1920 – v2010*.

2. E_i, is the environmental attributes, including neighbourhood and location characteristics:

- *Highway* is an indicator variable equal to one if the property is located within 500 metres buffer of the State Highway I, 0 otherwise;
- *DistanceCBD* represents the distance to CBD, measured in metres;
- *Popden* indicates population density, measured in kilometres/1000 people;
- *NZdep2013* is the NZ index of socioeconomic deprivation in 2013, ranges from 1 to 10, where 1 represents the areas with the least deprived scores and 10 the areas with the most deprived scores ; and
- *SchoolAchievement* represents the percentage of achieving NCEA level 3 in Year 13

3. YQ_i is a vector of year and quarter dummies to control for overall trends and seasonal fluctuations, including:

- *SaleYear* Year of sale of the property, 2003, 2004,……,2015
- *Q2* equal to one if the sale was in quarter 2, zero otherwise;
- *Q3* equal to one if the sale was in quarter 3, zero otherwise;
- *Q4* equal to one if the sale was in quarter 4, zero otherwise;

4. Before-After indicators:

- *Time* equals one if the property was sold after the opening of the Northern Busway (i.e. 2009-2015), zero otherwise;
- *Treated* equals one if the property was located within 2 km radius catchment area of the Northern Busway, zero otherwise[3];

[3] The catchment area is defined as 2 km based on walkable catchment analysis in Wilson (2013)

- *Time*Treated* is the interaction term, it equals one if the property was located within 2 km radius catchment area of the Northern Busway and sold after the opening of the Northern Busway.

Table 1 provides a brief description and a summary statistics for all variables included in final empirical model. On average, the property value was $648,482 at a size of 176 square metres with average land area of 716 square metres. More than 90% had a garage, 5% had a swimming pool, and a quarter's was crosslease. About 22% of all sold properties were in good interior condition, while only 3% were in poor interior condition. Around 14% of sales had an exterior appearance of monolithic plaster cladding, and approximately 20% had water views to some extent. Less than 10% of the sold properties' contour was not levelled. Nearly 80% were built in the last century. Around 7% of homes were located near State Highway I, and the average distance to CBD from the sample was close to 10 kilometres. The mean socioeconomic deprivation index for houses in the sample is just above three. With lower values representing more affluent neighbourhood (with 1 being least and 10 most deprived) this suggests that residents belong to higher socio-economic class. School achievement rate is represented by the percentage of students achieving NCEA level 3 in Year 13 with over 2/3 of students on average achieving this level. The low deprivation scores and high achievement rates is a frequent finding in the literature (for example see Caldas and Bankston 1997, White 1982). For the Before-After indicators, roughly half of the properties were sold before the opening of the Northern Busway, and the other half sold after the opening of the Northern Busway. Additionally, over one third were located in the catchment area, while 18% of those were sold after the opening of the BRT.

Table 1 Variables and Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
SalesPrice	648,482	419,092	40,000	6,960,000
ln(SalesPrice)	13.26	0.462	10.6	15.76
LandArea	716.0065	523.3	154	12,002
FloorArea	175.598	77.891	50	1,620
Garage	0.93	0.256	0	1

Pool	0.0522	0.222	0	1
Crosslease	0.253	0.435	0	1
InteriorGood	0.220	0.414	0	1
InteriorPoor	0.0257	0.158	0	1
Monoclad	0.136	0.343	0	1
WVwide	0.0742	0.262	0	1
WVmoderate	0.0618	0.241	0	1
WVsignificant	0.0665	0.249	0	1
Steep	0.09	0.286	0	1
v1910	0.0285	0.166	0	1
v1920	0.0270	0.162	0	1
v1930	0.0105	0.102	0	1
v1940	0.0246	0.155	0	1
v1950	0.0738	0.261	0	1
v1960	0.163	0.369	0	1
v1970	0.172	0.377	0	1
v1980	0.116	0.320	0	1
v1990	0.184	0.388	0	1
v2010	0.0220	0.147	0	1
Highway	0.0682	0.252	0	1
DistanceCBD	9,781	3,695	1,953	19,289
Popden	846.3	281.1	25.38	1,311
NZdep2013	3.233	1.812	1	10
SchoolAchievement	71.88	11.68	46.5	85
Sale year	6.467	3.794	1	13
Q2	0.265	0.441	0	1
Q3	0.22	0.414	0	1
Q4	0.24	0.427	0	1
Time	0.498	0.5	0	1
Treated	0.367	0.482	0	1

*Time*Treated*	0.177	0.382	0	1

6. Empirical Results

The estimated coefficients under non-spatial OLS-DiD, and spatial SARAR-DiD models with three different spatial weights matrices **C**, **6NN** and **8NN**, respectively, are reported in Table 3. First, we focus on the OLS-DiD results. Overall, all explanatory variables have expected signs, in accordance with earlier findings in the literature. The only exceptions are, *Popden*, *Garage*, *Monoclad*, *v1930* and *v1940*, which are insignificant. Specifically, it was not until 1950's when Auckland began to expand to the North Shore. Opening of the Harbour Bridge in 1959 triggered massive development of North Shore which was mainly farmland and sea-side villages before that. Therefore, bulk of housing was supplied from 1960's onwards hence insignificant result might be observed due to the low numbers of the house built in the 1930's and 1940's. In terms of property structures, as anticipated house prices increase as land and living area increase. Similarly, houses with pool, good interior quality, as well as with water views are higher valued. In contrast, poor interior quality and houses on steep land imply less value of a house. Moreover, as Bourassa *et al*. 1999, Beron *et al*. 2004, and Anselin and Lozano-Gracia, 2008 note, the relationship between property's age and price is non-linear. First, prices are higher for more recently built houses, which is reflected in the positive sign on *v2010* and negative signs on *v1950* to *v1990*. Second, there is also a vintage effect of property age on prices, which is reflected in the positive signs of the estimated coefficients for houses built before the decade of 1950.

In terms of neighbourhood and location characteristics, the estimated coefficient on *Highway* is negative, which implies the effect of the immediate vicinity to the highway is indeed a negative externality. As expected, the farther away from the CBD, the lower the value of a property. Deprivation is negatively correlated with house prices, where houses with lower deprivation index are higher priced. Higher school achievement rates also positively contribute to house prices. The year and quarter dummies are significant, and have expected signs. Property values increases every year over the sample period.

The overall fit of the OLS-DiD model is satisfactory, with an R^2 of 0.765 ($\bar{R}^2$ of 0.763). However, this specification suffers from high spatial autocorrelation, suggested by the estimated results of spatial autoregressive parameter, λ, and the spatial autocorrelation coefficient, ρ, towards the bottom of Table 3. It is evident that there is spatial dependence among the properties in our dataset under all forms of spatial weights matrices.

Next, few consider the three spatial models with difference weights matrices. Regarding signs, magnitudes and significances, most of the estimated coefficients from the SARAR-DiD models do not vary much compared to its non-spatial counterpart, with only exception of *Monoclad* and *v1940*, where the signs of the estimated parameter changed from positive under OLS-DiD, to negative under SARAR-DiD, with the use of nearest neighbours spatial weights matrices. Moreover, the R^2 and $\bar{R}^2$ of all the spatial models are marginally higher compared to the one in OLS, which suggest that including spatial variability enhance the explanatory power of the model.

Table 2 OLS-DiD and SARAR-DiD Estimation Results (dependent variable = log of net sales price)

	OLS-DiD		**SARAR-Did**	
VARIABLES		*C*	*6NN*	*8NN*
Constant	12.08***	12.101***	12.106***	12.111***
	(0.0562)	(0.0544)	(0.0537)	(0.0540)
LandArea	0.000102***	0.000108***	0.000106***	0.000104***
	(1.29e-05)	(1.32e-05)	(1.32e-05)	(1.30e-05)
FloorArea	0.00176***	0.00172***	0.00170***	0.00171***
	(0.000336)	(0.000326)	(0.000321)	(0.000323)
Garage	0.0218	0.0219	0.0217	0.0220
	(0.0139)	(0.0136)	(0.0135)	(0.0136)
Pool	0.144***	0.136***	0.137***	0.139***
	(0.0220)	(0.0214)	(0.0213)	(0.0214)
Crosslease	-0.0734***	-0.0718***	-0.0726***	-0.0730***
	(0.00989)	(0.00971)	(0.00957)	(0.00960)
InteriorGood	0.101***	0.0988***	0.0979***	0.0981***
	(0.0208)	(0.0201)	(0.0197)	(0.0198)
InteriorPoor	-0.128***	-0.120***	-0.119***	-0.122***

	(0.0267)	(0.0256)	(0.0255)	(0.0246)
Monoclad	0.00354	0.000014	-0.000638	-0.00051
	(0.0132)	(0.0128)	(0.0125)	(0.0126)
WVwide	0.268***	0.244***	0.239***	0.238***
	(0.0240)	(0.0224)	(0.0221)	(0.0222)
WVmoderate	0.133***	0.128***	0.128***	0.128***
	(0.0174)	(0.0168)	(0.0166)	(0.0166)
WVsignificant	0.0766***	0.0703***	0.0696***	0.0701***
	(0.0150)	(0.0143)	(0.0141)	(0.0142)
Steep	-0.0543***	-0.0469***	-0.0457***	-0.0474***
	(0.0117)	(0.0113)	(0.0111)	(0.0112)
v1910	0.284***	0.249***	0.242***	0.242***
	(0.0336)	(0.0325)	(0.0321)	(0.0320)
v1920	0.138***	0.124***	0.123***	0.124***
	(0.0348)	(0.0341)	(0.0339)	(0.0339)
v1930	0.0702	0.0688	0.0560	0.0593
	(0.0468)	(0.0455)	(0.0463)	(0.0465)
v1940	0.00738	-0.0169	-0.0301	-0.0268
	(0.0398)	(0.0383)	(0.0375)	(0.0375)
v1950	-0.0562*	-0.0609**	-0.0690**	-0.0675**
	(0.0305)	(0.0294)	(0.0292)	(0.0293)
v1960	-0.154***	-0.148***	-0.152***	-0.153***
	(0.0249)	(0.0239)	(0.0239)	(0.0239)
v1970	-0.164***	-0.153***	-0.156***	-0.157***
	(0.0238)	(0.0231)	(0.0230)	(0.0231)
v1980	-0.119***	-0.118***	-0.120***	-0.120***
	(0.0245)	(0.0239)	(0.0236)	(0.0236)
v1990	-0.0941***	-0.0959***	-0.101***	-0.101***
	(0.0201)	(0.0195)	(0.0197)	(0.0197)
v2010	0.0505**	0.0536**	0.0439**	0.0434**

	(0.0213)	(0.0214)	(0.0207)	(0.0207)
Highway	-0.0237**	-0.0217**	-0.0210**	-0.0222**
	(0.0105)	(0.0103)	(0.0104)	(0.0104)
DistanceCBD	-1.96e-05***	-1.90e-05***	-1.90e-05***	-1.90e-05***
	(1.17e-06)	(1.21e-06)	(1.21e-06)	(1.22e-06)
Popden	-4.10e-07	-4.00e-06	-4.00e-06	-4.00e-06
	(1.51e-05)	(1.38e-05)	(1.63e-05)	(1.56e-05)
NZdep2013	-0.0256***	-0.0258***	-0.0259***	-0.0256***
	(0.00219)	(0.00214)	(0.00213)	(0.00213)
SchoolAchievement	0.00851***	0.00814***	0.00823***	0.00814***
	(0.000457)	(0.000464)	(0.000465)	(0.000485)
SaleYear	0.0915***	0.0912***	0.0916***	0.0914***
	(0.00194)	(0.00187)	(0.00186)	(0.00186)
Q2	0.0241***	0.0227***	0.0210**	0.0207**
	(0.00905)	(0.00866)	(0.00856)	(0.00855)
Q3	0.0535***	0.0516***	0.0507***	0.0492***
	(0.00946)	(0.00920)	(0.00913)	(0.00912)
Q4	0.0548***	0.0543***	0.0502***	0.0500***
	(0.00907)	(0.00876)	(0.00864)	(0.00865)
Time	-0.261***	-0.254***	-0.258***	-0.255***
	(0.0147)	(0.0146)	(0.0146)	(0.0146)
Treated	-0.0585***	-0.0569***	-0.0591***	-0.0579***
	(0.0107)	(0.0111)	(0.0113)	(0.0113)
*Time*Treated*	0.0385***	0.0394***	0.0392***	0.0389***
	(0.0130)	(0.0132)	(0.0132)	(0.0133)
λ		0.00237*	0.00298**	0.00317***
		(0.00123)	(0.00139)	(0.00152)
ρ		0.546***	0.623***	0.658***
		(0.0390)	(0.0368)	(0.0417)

Observations	4,674	4,674	4,674	4,674
R^2	0.765	0.779	0.783	0.782
$\bar{R}^2$	0.763	0.777	0.781	0.781

Note: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The positive and significant λ and ρ suggesting that the spatial dependence among the properties, and is in the expected direction: a positive neighbouring effect. A positive λ is also under expectation since, for instance, a higher average sale price of nearby properties should lead to a higher sale price of a certain property, *ceteris paribus*. λ is significant at a 1% level and robustly estimated at a range of 0.00237 to 0.00317 across all the specifications, indicating that if the weighted average of neighboring houses' sale price increases by 1%, the sale price of an individual house increases by approximately 0.002% to 0.003%.

Regarding the interpretation of the regression coefficients, in the spatial models, marginal effects should be calculated by multiplying the estimated coefficients with a spatial multiplier, defined by Kim *et al*. (2003), as $1/(1-\lambda)$. A larger λ implies a larger spatial dependence and, thus, a larger spatial multiplier. For our study, the values of the spatial multipliers are 1.00238, 1.00299 and 1.00318 under three different scenarios of spatial weights matrices **C**, **6NN** and **8NN**, respectively. It is also important to note that the estimated marginal benefits represent the capitalised, rather than the annual value of the benefits of change in infrastructure amenities. The estimated percentage changes, or elasticities, of Before-After indicators under OLS-DiD and SARAR-DiD models are summarised in Table 3.

Table 3 Estimated Percentage Change for Before-After Indicators under DiD models

Variable	OLS-DiD	SARAR-DiD-C	SARAR-DiD-6NN	SARAR-DiD-8NN
Time	-0.2297	-0.2238	-0.2266	-0.2247
Treated	-0.0568	-0.0552	-0.0572	-0.0561
*Time*Treated*	0.0393	0.0401	0.0399	0.0396
*Treated+Time*Treated*	-0.0176	-0.0151	-0.0173	-0.0166

The estimated results from Table 3 can be used to derive the MWTP. Following Halvosen and Palmquist (1980), Crane *et al*. (1997), Kim *et al*. (2003) and Diao (2015), the MWTP for a particular property attribute g can be computed by:

$$\widehat{MWTP} = \widehat{\beta_g} \ * \overline{p}$$

where $\widehat{\beta_g}$ represents the estimated percentage change of Before-After attributes from Table 3, and $\overline{p}$ is the mean property price in the sold sample ($648,482). The estimated MWTP for the Before-After indicators under the SARAR-DiD models are summarised in Table 4.

Table 4 Estimated MWTP from the DiD Models

Variable	OLS-DiD	SARAR-DiD-C	SARAR-DiD-6NN	SARAR-DiD-8NN
Time	-$148,969	-$145,115	-$146,923	-$145,690
Treated	-$36,848	-$35,783	-$37,096	-$36,391
*Time*Treated*	$25,453	$25,998	$25,848	$25,654
*Treated+Time*Treated*	-$11,394	-$9,785	-$11,248	-$10,737

Several main findings are observed from the estimated results in Table 3 and Table 4. Firstly, the absolute values of estimated percentage (and hence the estimated MWTP) from *Time*, *Treated* and *Treated+Time*Treated* attributes based on OLS are generally higher than those based on spatial estimators, with only one exception for *Treated* under the spatial model with 6NN. These results are in line with previous real estate literature, which propose that upward bias is found when the spatial characteristics of the data are not controlled for, suggesting an over-estimation of the non-spatial OLS method (Pace and Gilley, 1998; Kim *et al*. 2003; Tsutsumi and Seya 2009, Koschinsky *et al*., 2012). Second, the percentage change and the associated MWTP for *Time*Treated* estimates of all of the spatial models are larger than in the OLS case, implying the impact of the exogenous change of infrastructure amenity on the property prices are underestimated when spatial dependence is not taking into account. Third, for all three spatial models, the average net sale price for properties within 2 km radius catchment area (i.e. treatment group) on the North Shore increases by approximately 4% (or around $25,654 to $25,998) as a result of the opening of the Northern Busway (from before to after). Last, the price gap between the treatment group and the control group has also been shrinking thanks to the opening of the Northern Busway. Specifically, before the opening of the Northern Busway, the average net sale prices of the properties within 2 km radius catchment area is almost 6% (or $35,783 to $37,096) lower compared to the rest of properties sold on the North Shore (i.e. control group). After the opening of the Northern Busway, the average net sale price for all sold properties within 2 km radius catchment area is only 2% (or $9,785 to $11,248) lower compared to the rest of properties sold on the North Shore.

7. Conclusion

This study improves on past hedonic modeling literature by explicitly incorporating spatial effects into the hedonic model under DiD framework. It uses a SARAR-DiD model to quantitatively evaluates the incremental effects of proximity of residential property to Northern Busway, the first BRT in Auckland, New Zealand over time. The SARAR-DiD hedonic model deals with neighborhood effects that cannot be captured by non-spatial OLS technique. By comparing the results of different models, the spatial models not only fit the data better than OLS estimates by taking account of spatial effects, but also corrects the econometric problems of over/under-estimation bias generated by its non-spatial counterpart.

While controlling for other price determinants including neighbourhood and locational attributes as well as property structure characteristics and seasonality, the empirical results from all SARAR-DiD models indicate that the property price gap between the catchment areas and control areas is a round shrinking although the impact is still negative. Specifically, properties in the catchment area are sold at a discount in comparison with the control properties, but the benefits are beginning to capitalise into house prices after the commencement of the BRT. Second, prices of properties adjacent to the motorway and hence busway line suffer from negative externalities such as noise and congestion. Last, in line with Grimes and Yong (2013), it has been shown that positive amenity value associated with town centre redevelopment can outweigh negative externalities. This property value uplift is identified for the benefits in accessibility offered by BRT as the effect of time and other impacts are controlled by the time dummies and catchment dummies (interaction terms) in the model.

This study supports conclusions found in previous research in relation to bus-based value uplift: accessibility improvements do encourage an upsurge in property values but the increase is not substantial. Moreover, the study confirms that properties located too close to motorway and hence busway infrastructure are discounted due to the negative externalities. This is a repeated argument in other studies that negative externalities arising from close proximity such as noise, congestion and concerns around security depress house prices. Positively, BRT brings accessibility benefits to nearby residents. This is evident in increasing ridership and diminishing discount of proximity to stations since the busway was introduced. However, the evident drop-off in value can be remedied with provision of positive amenities such as redevelopment of nearby land (Grimes and Young 2013). Therefore, from the policy point of view effective land use and transportation policies can help alleviate the negative effects of proximity to stations.

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