RESIDENTIAL PROPERTY VALUE IMPACTS OF PROXIMITY TO TRANSPORT INFRASTRUCTURE: AN INVESTIGATION OF BUS RAPID TRANSIT AND HEAVY RAIL NETWORKS IN BRISBANE

ABSTRACT

Public transport investment is normally targeted at increasing accessibility which land rent theory identifies will in turn increase land values. There is clear policy interest in how much land values increase following a new transport investment so as to establish if there is sufficient land value uplift to capture to help pay or contribute to investment plans. Identifying uplift for residential land has been well studied in the context of new light rail systems and bus rapid transit (BRT) systems in developing countries but there is little evidence for BRT in developed countries.

This paper has two objectives. First, to examine long term impact of BRT in a developed world context in Brisbane, Australia as studies in Sydney, Australia. This provides an addition to the BRT literature in developed countries where the only other suggests little uplift in comparison to developing world contexts. Second, to consider the spatial distribution of uplift which is an essential pre-requisite to understanding the distributional impact if uplift is used to contribute to infrastructure provision.

Spatial modelling is used to examine the accessibility impacts of the BRT and this is followed by Geographical Weighted Regression, used to examine the spatial distribution of accessibility.

The results show there is greater uplift in Brisbane, as compared to Sydney, Australia which is likely due to the greater network coverage of BRT in Brisbane and a relative lack of rail based competition. Land value uplift is also spatially distributed over the network giving higher uplift in some areas than others and lower values than typically found with rail based systems in developed countries.

Highlights

- Being close to BRT adds a premium to the housing price
- The price premiums varies over space
- High-frequency feeder bus network appears to be the key for the capitalization effects
- GWR improves spatial models by accounting for spatial non-nonstationarity

Keywords

Bus Rapid Transit; Spatial Modelling; Geographical Weighted Regression; Brisbane, land value uplift, land value capture

1. Introduction

Discussions around land rents and land values have been a feature of urban economics for more than a century. From the nineteenth century, economists like David Ricardo were concerned with the potential outcome of land being a non-produced input and the impact this might have on wages (Ricardo, 1821). More modern economics recognises that land rent, as with the ‘return’ on other goods, reflects the marginal productivity of land(Trivelli, 1997). Within a transport infrastructure value context, the contemporary interest in land value stems from two related issues. First, can and by how much does land value rise if new transport infrastructure is implemented? Second, given the increasingly apparent funding constraints faced by governments around the world, can any increase in value of land as a result of implementing new transport infrastructure be “captured’’ to pay for the investment? This paper addresses the first of these issues as a pre-requisite to informing the second.

Whereas most of the value uplift literature has been concerned with either developed countries or with the introduction of rail based infrastructure, this paper will consider whether and to what extent the value of residential land has increased in the area around a bus rapid transit (BRT) network constructed in the low density city of Brisbane, capital of the Australian state of Queensland. This paper also adds to the literature by modelling the spatial variation of this uplift. An understanding of the spatial variation of value uplift is necessary to design better value capture policies.

The paper is structured as follows, section 2 summarises the literature on value uplift theory; section 3 introduces the case study area of Brisbane, Australia; section 4 discusses the methodology and section 5 presents the results of the geographically weighted regression analysis to determine the extent of value uplift associated with the BRT development before section 6 discusses the policy implications of the findings.

2. Literature Review

Land rent theory provides the theoretical link between accessibility and land values with land rent reflecting the underlying accessibility. As a result, those locations which are more accessible as a result of new infrastructure will command a higher rent reflecting the underlying land value and include the value uplift. A complication is that the theory is developed in the context of unimproved land, referring to land with no structures on it whereas in an urban context we observe primarily land with structures. This means that a methodology needs to be developed that controls for the improvements to land so as to expose the changes in land values due to accessibility changes arising from new transport infrastructure. Issues concerning methodology are discussed in the methodology section below.

There is significant international interest in determining uplift that can be delivered by the implementation of new transport infrastructure, as a baseline for understanding what values may be ‘captured’ in specific ways by local and state agencies for funding and financing purposes.Although the earliest studies were more qualitative (Knight and Trygg, 1977), there have been a plethora of studies since 2000 which have been concerned with identifying the value uplift. RICS (2002), Smith and Gihring (2006) and Smith et al. (2009)have provided major reviews of the studies examining value uplift. Billings (2011) identifies the presence of at least 20 studies across five countries on the impact of rail investments with Debrezion et al. (2007)presents meta analyses fromthe real estate literature. Debrezion et al. (2007)used 73 studies and focused on the impact of railway stations on land values and the results suggest that for every 250m closer to a station, house prices increase by 2.4% whereas commercial properties only increase by 0.1%. This points to a major difference between residential and commercial properties with the latter probably internalising the uplift from before the operational phase or, alternatively, reflecting the way planning rules extract much of the uplift with judicious use of planning gain with new commercial build. Zhang (2009) separates houses from apartments and found that single family homes appeared to benefit much more from value uplift although with considerable variability with for example, the impact for an apartment in 1990 US$

being$0.3 uplift butfor a single family home this varied between $0 and $38 for every meter further away from the BRT. This stark difference suggests that there is a difference between the different types of property's ability to benefit from uplift and that any analysis should take this into account. A more recent update, concerned with specifically Asian cities, is provided by Salon and Shewmake (2011), and this highlights the great variability in conclusions of the different studies, in part due to the method adopted in investigating value uplift (this issue is expanded upon in the methodology section below).

Most of the literature cited above, or used in the meta-analyses, arebased on the introduction of rail based systems: light rail, heavy rail or metro. This paper is focused on the contribution of bus rapid transit (BRT). The contribution this relatively new mode can make to value uplift is an area that is neglected in the literature with few notable exceptions. There have been studies on the BRTs in large cities in developing countries with studies by Rodríguez and Targa (2004) finding an uplift of between 6.8% and 9.3% for every five minutes closer to a station on the Transmilenio in Bogota, Columbia and Munoz-Raskin (2010) finding very variable results both close and further away from Transmilenio. Rodríguez and Mojica (2009) investigated the impact of the BRT extension in Bogota and found that properties in the environs of the extension had values 13-14% higher than in control areas but no appreciable difference between prices close and not so close to the BRT. As the appeal of BRT has spread, so have the studies investigating value uplift from BRT and now there is evidence from Beijing, China (Deng and Nelson (2010) finding 2.3 percent annual growth premia for properties close to the BRT), Seoul, Korea (Cervero and Kang (2011)finding up to 10% uplift for residential properties and Jun (2012) finding negative premia in suburban areas). The results of Jun (2012)suggesting lower uplift in suburbia ties in with one study from Australia (Mulley, 2014) which looked at a BRT that was part of a wider network of 'ordinary' buses set in the suburbs of Sydney, NSW. Other developed country studies have found very variable results with reported uplift in Pittsburgh, US, of around 16% (Perk and Catala, 2009)and between 2.9% and 6.9% in Quebec, Canada (Dubé et al., 2011).

This study is concerned with the extensive BRT in the conurbation of Brisbane in Queensland. Australia. Unlike its BRT counterpart in Sydney, and to a lesser extent in cities with BRT in the US, the Brisbane BRT is the backbone of the public transport system in Brisbane, travelling to the heart of the city with its dedicated infrastructure. Its network design includes feeder services traversing the suburban neighbourhoods before entering the dedicated infrastructure to travel to the CBD. In this way the network design is distinctively different from the successful systems of developing countries which tend to have services travelling simply on the BRT infrastructure with feeder services travelling to the BRT. This study is concerned with residential properties only as the literature review identifies differences between commercial and residential properties with a distinction being made in the empirical analysis to treat apartments and houses as different 'goods'.

3. Unique characteristics of Brisbane BRT

This section will introduce Brisbane with the South East Queensland region before comparing the extent and service levels of the BRT and rail networks that are focussed on the Brisbane city centre. Mention will also be made of the non-BRT bus services that also operate in the area and are included in the modelling presented in Section 5.

3.1 Brisbane and South East Queensland

Brisbane is the capital of the Australian state of Queensland and has an urban population of 2.2 million (Australian Bureau of Statistics, 2015). Brisbane accounts for 70% of the population of the greater South East Queensland (3.1 million) area which includes the Gold and Sunshine Coasts. Brisbane itself comprises 5 local government areas (LGAs), the biggest of which is Brisbane City Council with a 2014 population of 1.1 million (Australian Bureau of Statistics, 2015).

Public transport in South East Queensland is operated under the TransLink brand with the state government responsible for planning and regulating services. Public transport services are operated by a mixture of private bus operators (who operate mostly outside the Brisbane City Council area), the Queensland government (the Queensland Rail City Network, formerly Citytrain)and the Brisbane City Council owned bus operator called Brisbane Transport. A number of ferry services are operated by Transdev on behalf of Brisbane City Council and are included in the TransLink network. An integrated fare system operates across the bus, train and ferry networks.

Australian public transport networks are highly radial in nature. The South East Queensland network follows this pattern with patronage and service levels concentrated on the Brisbane city centre or Central Business District (CBD) far in excess of the share of employment, population and activities that actually occurs in the CBD. Partly, this is due to geography with most crossings of the Brisbane River either being near the CBD or on the Eastern and Western periphery of the urban area. However, the concentration of services on the CBD also reflects the historic pattern of development of public transport services. As a result, in 2009 Brisbane residents made 84% of the public transport journeys in South East Queensland(Queensland Government, 2012).

Outside of the Brisbane City Council area, the rail network remains radially focussed on the Brisbane CBD but the bus networks become more focussed on local centres or railway stations with radial bus services not extending beyond the boundaries of the Brisbane urban area.

3.2 The Bus Network and BRT System

Brisbane's 32km busway network services the inner and middle suburbs of Brisbane, with most services focussed on the CBD but with significant cross regional services to the University of Queensland. Under Vuchic's (2007) definitions the Brisbane busways are almost entirely Category A, provided with fully segregated and physically protected rights-of-way. This includes significant grade separation both above the surface street network, particularly along the South East Busway, and large underground systems, including the inner Northern busway, the King George Square and Queen Street bus stations, and parts of the Eastern busway. For only around 400m total and three intersections in South Brisbane and at North Quay does the system revert to bus-lanes and interface with other traffic.

The 27 busway stations are spaced on average 1.2km apart with more distance between stations at the periphery and closer spacing near the city centre. Given its two-lane rights-of-way supporting 80km/h travel on most of the network, and with passing lanes at all busway stations, the 'Quickway' model of bus rapid transit is possible(Hoffman, 2008). This provides for a wide range of routes (some stopping all stations, others express) that branch off along the busway corridor to service surrounding suburban areas some distance away, with many bus routes drawing patronage away from Brisbane's rail network. Single-seat journeys are standard as most services are through-routedto the city centre with almost no feeder buses, although significant numbers of passengers interchange at busway stations for services to the University of Queensland.

The system is relatively mature, with the first sections opened in the year 2000. Over 300 buses per hour travel on key links of the South East Busway, carrying over 20,000 passengers per hour in the peak, not far from the theoretical limit of BRT operations. The system carries more than 70 million passengers per year mostly on Brisbane City Council's bus fleet. Most buses are two-door, rigid buses carrying around 62 passengers maximum, with a small number of articulated buses of around 85 persons capacity in operation. Almost all of the fleet runs on compressed natural gas. Expansions are planned to the North, South and East in future years. To overcome capacity constraints in the city centre a second busway river crossing is proposed, though a recent option to complete this as part of a cross-river rail tunnel was shelved in early 2015.

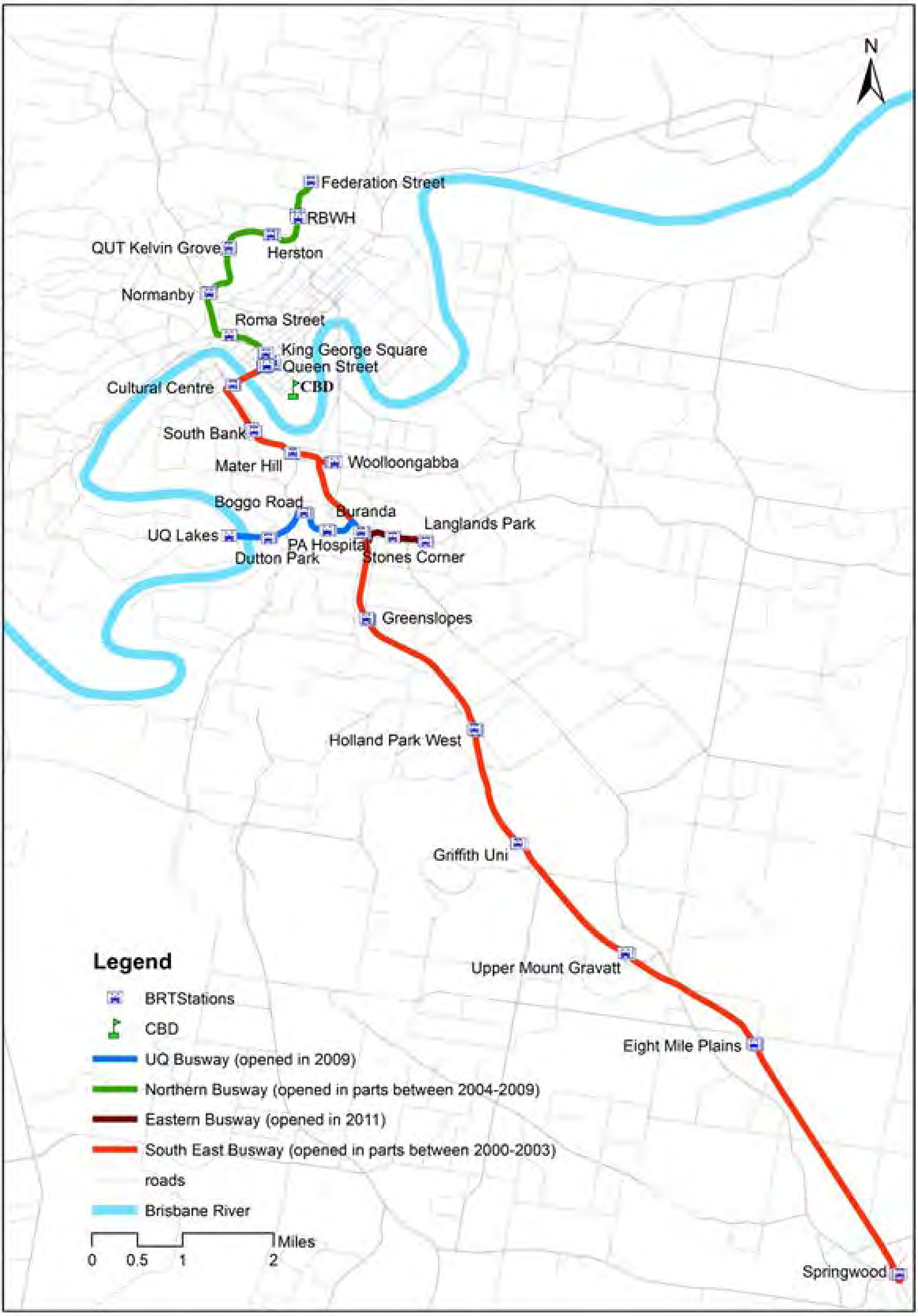

Figure 1 The BRT system in Brisbane in 2011.

3.3 The South East Queensland Train Network

By contrast,Brisbane's CityRail network stretches to the neighbouring cities of the Gold Coast and Sunshine Coast, and out to Ipswich, with over 600km of track and over 220km of serviced route(Soltani et al., 2015). At the time of writing there are 146 stations though a 13km and six station extension to Kippa-Ring from Caboolture will open in early2016. Since the closure of the Tennyson line in 2011, the train network is entirely radial with eight lines connecting in the central business district. The system is electrified and uses 214 electrical multiple units in three car sets, usually configured together as six car trains capable of holding 480-520 passengers each. They operate at up to 130km/h though alignments and stop spacings in the suburban network reduce maximum speeds to much lower levels. Though there has been fare-free transfers on the whole public transport network since 2004, very few stations are serviced by feeder buses, especially in the Brisbane City Council jurisdiction where its buses mostly head towards the busways.

3.4 Levels of Service – bus versus train

As discussed above, maximum usage of the busway infrastructure is made by combining trunk busway services with, what would be in other jurisdictions, feeder bus services to provide single seat journeys. Many of the over 100 busway routes operate as peak hour expresses or at lower frequencies during the day but many busway routes form part of Translink's frequent network that consists of 9% of bus routes by 44% of the bus patronage. Within Brisbane, the frequent network is marketed under the Bus Upgrade Zone (aka 'BUZ') introduced by Brisbane Transport in 2003 (Neelagama, 2014) or the CityGlider concept introduced in 2010. There are 20 BUZ routes that operate throughout Brisbane with maximum 15 minute headways between 06.00 and 23.00 all week and a maximum headway of 10 minutes in weekday peak periods (07.00 to 09.00 and 16.00 to 18.00). Headways are similar on the rest of the frequent bus network in South East Queensland but the span of hours is shorter outside the Brisbane City Council area. The CityGlider services are pre-paid services that offer boarding from both front and back doors and operate with a similar frequency and span of hours to the BUZ routes but also operate overnight services on Friday and Saturday nights (i.e. Saturday and Sunday morning).

Like a train network, the Brisbane busway network has offered passengers faster, more frequent and reliable bus services. Consequently, busways have helped to uplift bus service quality and make bus more significant influence on trip frequency than other public modes (Devney, 2014). In contrast, train services normally operate at 30 minute headways off peak in the outer suburbs and 15 minutes (or better) headways have only slowly been implement in the inner suburbs. Consequently, the train network has a relatively low level of patronage compared to the busway network. In 2013, the mode shares for bus, train, and ferry were 54%, 44% and 2%, respectively(BITRE, 2013). Figure2 shows the historical trends in Brisbane from 1900 to 2013.

From the opening of the first section of the busway, between the CBD and Woolloongabba in September 2000, and the second section between Woolloongabba and Eight Mile Plains in April 2001, there has been an upward trend in patronage. Figure 2 shows the busway and heavy railway passenger numbers in Brisbane from 1999 to 2013 and excludes the extension of the busway to Springwood, which was completed in mid-2014. In sharp contrast to the heavy railway service, the busways have achieved an increasing market share and patronage growth. The total number of public transport passengers in Brisbane has increased from approximately 91 million in 1999 to 148 million in 2013. Whilst train patronage has risen significantly in other Australian cities, especially Melbourne, in Brisbane patronage has stagnated. Figure 2 suggests that the development of busways has had considerable competitive effects on the train system by taking significant market share.

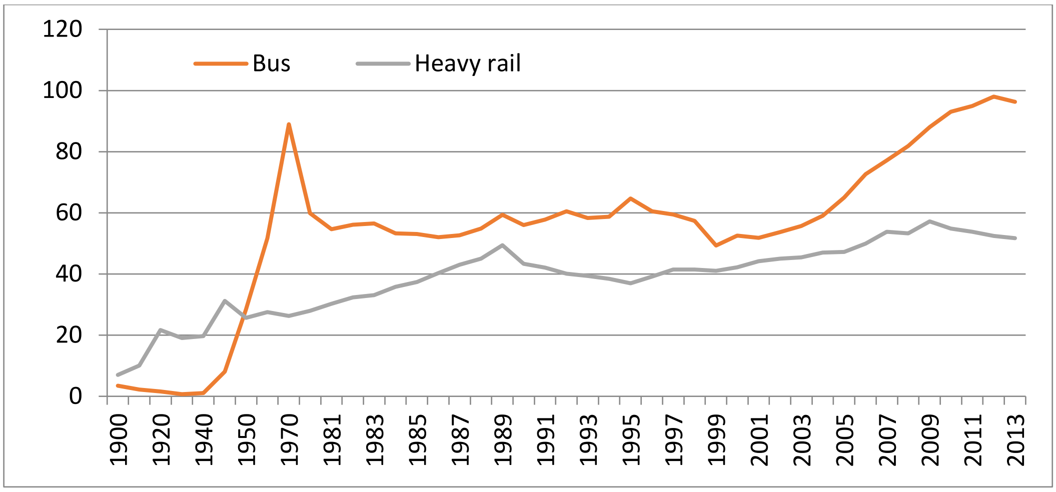

Figure 2 Historical trends in public transport patronage (millions of passengers), Brisbane, 1900 to 2013.
Source: Cosgrove (2011), BITRE (2012)and BITRE (2014).

4. Methodology

The literature review identifies quite divergent results. In part this is due to different methodologies in use as well as the different locations of the studies. The earliest literature in this domain borrowed methodology from experimental studies to provide simple before and after studies, some with control areas and some using difference in difference models. These were not particularly well related to the way in which the theory relates to unimproved land since most did not take the specific features of the property into account. Moreover, whilst these quasi-experimental approaches explored temporal differences they could not include the nuances of environmental and socio-economic factors. More sophisticated methodologies have been developed using hedonic modelling or Ordinary Least Squares (OLS) regression following Lancaster (1966)who argued that a good can be broken into its constituent attributes with implicit prices and Rosen (1974) who showed how this could be implemented in the housing market. However, the early hedonic modelling did not take account of the way in which the data used to investigate the uplift due to new transport infrastructure is inherently spatial in nature and that this could (and did) lead to violations in the OLS assumptions. More recent papers have taken advantage of panel data when repeat sales data are available and the large suite of spatial models which have become easier to implement through software developments. Salon and Shewmake (2011) provide a succinct review of available methodologies and comment that many of the studies they examined did not acknowledge the possibility of spatial dependence. This paper uses a number of approaches to control for the spatial dependence of the data which are explained in the next sub-section. This is followed by a description of the data and its descriptive statistics.

4.1 Model Specification

First, a standard hedonic pricemodelis estimated using a semi-log functional form to provide better behaved errors. The dependent variable is defined as the natural log of sale price of the property in a model formulation as follows:

$$LnP = c + \sum a_3\boldsymbol{X}_s + \sum a_2\boldsymbol{X}_n + \sum a_1\boldsymbol{X}_l + \sum a_0\boldsymbol{X}_p + \varepsilon \qquad (1)$$

where P is the sale price of the residential property; X_s, X_n and , X_l refer to structural characteristics of the property, socio-economic conditions, and neighbourhood features due to the location of the property respectively; and X_p refers to proximity to transit stations. In this equation, $a_0 a_1$ a_2 and a_3 are the coefficients to be estimated; c is the model constant, and ε is the residual error.

As discussed above, the analysis of the spatial variations of the housing price using standard OLS estimation presents certain challenges. As well as the effects included in equation (1), the house price is often influenced by the price of nearby properties which typically share the similar structural and locational characteristics as described in equation (1) giving rise to OLS residuals being spatially dependent.In these cases the OLS model results are biaseddue to the violations of the assumptions.A spatial lag and a spatial error model with spatial weighting matrices are employed next to compare and correct for the potential problems with the OLS model.The spatial lag model can be expressed as:

$$LnP = c + \boldsymbol{\rho W}P + \sum a_3\boldsymbol{X}_s + \sum a_2\boldsymbol{X}_n + \sum a_1\boldsymbol{X}_l + \sum a_0\boldsymbol{X}_p + \varepsilon \qquad (2)$$

Where the ρWP measures the spillover effects which occur when the housing price of a property is influenced by the price of other properties. W is a matrix of spatial weights, and the ρ is the parameter measuring the degree of spatial correlation.

The spatial error model assumes the error term has two parts: one is an independent and identically distributed spatially uncorrelated component μ, the other is a spatial component$\lambda W\varepsilon$. λ is thespatialerror coefficient. The model can be expressed as:

$$LnP = c + \sum a_3\boldsymbol{X}_s + \sum a_2\boldsymbol{X}_n + \sum a_1\boldsymbol{X}_l + \sum a_0\boldsymbol{X}_p + \boldsymbol{\lambda W}\varepsilon + \mu \qquad (3)$$

Both the spatial lag and spatial error models can be estimated using Maximum Likelihood. Though the spatial lag and spatial error models help to control for spatial dependence, the results show that they did not deal with the spatial nonstationarity.

In the next stage, Geographically Weighted Regression (GWR) was employedto take into account both spatial dependence and spatial nonstationarity(Fotheringham et al., 2003). GWR outperforms the traditional hedonic price model and other spatial modelling by internalising the spatial dependence in the estimation process and mapping the results of local statistics(Mulley, 2014). By visualizing the spatial patterns of the relationship between dependent and independent variables, in this case, the relationship between property values and accessibility to the BRT stations, GWR helps the researchers to better understand the context-based factors contributing to the relationship, and offers informative results beyond global models to facilitate place-specific planning policy decisions.

The GWR local model expands the OLS model of equation (1) by allowing parameter values to vary with geographical location $\boldsymbol{u}_i(= (u_{xi,}u_{yi}))$ which is a vector of two dimensional co-ordinates describing the location of$i$. The GWR model can then be written as:

$$LnP_i = c(\boldsymbol{u}_i) + \sum a_3(\boldsymbol{u}_i)\boldsymbol{X}_{si} + \sum a_2(\boldsymbol{u}_i)\boldsymbol{X}_{ni} + \sum a_1(\boldsymbol{u}_i)\boldsymbol{X}_{li} + \sum a_0(\boldsymbol{u}_i)\boldsymbol{X}_{pi} + \varepsilon_i \qquad (4)$$

The GWR model is estimated using the geographically weighted maximum likelihood principle (Nakaya, 2001). Following this method, the local model is estimated using the observations within a bandwidth and by solving a maximization problem of geographically weighted likelihood. The geographical weight, w_{ij}, is a function of the distance away from the regression point i. The observations that are close to regression point are given higher weighting than those further away. The classical choice of weighting scheme is the Gaussian kernel defined by

$$w_{ij} = \exp(-d_{ij}^2/\theta^2)$$

where d_{ij} is the Euclidean distance between i and j. θ is a fixed bandwidth size defined by a distance metric measure. In this scheme, the geographical extent for estimating local models is constant over space. As an alternative, an adaptive weighting approach allows the spatial extent to vary at different regression points, in order to include the same number of sample points for each local regression model. The popular adaptive kernel, the bi-square kernel, is defined by

$$w_{ij} = \begin{Bmatrix} \left(1 - d_{ij}^2/\theta_{i(k)}\right)^2 d_{ij} < \theta_{i(k)} \\ 0 \qquad\qquad\qquad d_{ij} > \theta_{i(k)} \end{Bmatrix}$$

where $\theta_{i(k)}$ is an adaptive bandwidth size defined as the k th nearest neighbour distance. Considering the relatively large variation in the geographical density of the observed data, an adaptive weighting approach for this study. To select the ideal bandwidth size, different models with different bandwidth sizes are compared using the model selection indicator, AICc (sample size bias corrected Akaike information criterion).

GWR has the great strength of allowing the spatial variations of the proximity effects to be visualised on maps. However, it presents certain challenges in estimating the local coefficients. Local collinearityis identified as a major constraint in the use of GWR that can have a serious impact on the local coefficients estimations(Wheeler and Tiefelsdorf, 2005; Wheeler, 2007).The local collinearity problem is usually introduced when a restricted sampleis used for GWR local model estimation andwherethe observations within this restricted sample share similar characteristics, such as property type, structure, and neighbourhood amenities(Bárcena et al., 2014).The outcome is that standard errors can be inflated and/or more seriously parameter estimates can change signs.

Whenever this local collinearity presents as a problem, the GWR with a ridge regression parameter is proposed and validated as an effective way to reduce the effect of local collinearity on the model(Wheeler, 2007). Ridge regression in general is a method to reduce the adverse effect of collinearity in a model (Hoerl and Kennard, 1970). By penalizing the size of coefficients, the implementation of a ridge regression reduces the influence of the variables with relatively small variance (Gollini et al., 2013; Wheeler, 2007; Wheeler and Waller, 2009). The estimator for the locally compensated ridge GWR model can be specified as:

$$\hat{\beta}(\boldsymbol{u}_i) = \left(X^{\mathrm{T}} W(\boldsymbol{u}_i) X + \lambda I(\boldsymbol{u}_i)\right)^{-1} X^{\mathrm{T}} W(\boldsymbol{u}_i) Y$$

where$\lambda I(\boldsymbol{u}_i)$ is the locally-compensated value of λ at location $\boldsymbol{u}_i$.

4.2 Dataand Variables

The property transaction data used in this study was provided by RPdata, a commercial firm which combines data from different sources to provide details of the transaction information of the properties, including transaction price, property type (house or unit), area size, number of bedrooms, bathrooms and parking places, and latitude/longitude of the property. Considering the unique feature of the Brisbane BRT system, which includes extensive feeder bus services to the trunk bus route, a relatively big buffer (5-kilometer) is used to define thestudy area. All properties sold in 2011 that are in this 5-kilometer buffer of the BRT trunk line were selected foranalysis.

The selected properties were geocoded in GIS using the coordinateinformation. The street network distances to the BRT stations (*DBRT*) and train stations (*DTrain*) were calculated using network analysis. The euclidean distance from the property to the CBD (*DCBD*) and river (*DRiver*) were measured to indicate the regional location characteristicand accessibility to waterfront area of the property which is hypothesised to increase the value of a property. The number of common destinations (*Amenities*), such as restaurants, cafés, hospitals, libraries, pharmacies, fastfood shops, cinemas, banks, child care, etc., within 400 meters was calculated as an indicator of local amenitieswithin walking distance of the property with the hypothesis that a higher number of amenities would add to property price. Further, the census data collected at SA1 level (the smallest geography available) were spatially joined by the properties to acquire the neighbourhood characteristics including population density (*PopDen*), percentage of older people (*Older*), and median weekly household income (*HHincome*).Table 1 provides the descriptive statistics for these variables.

Table 1Descriptive statistics for the dependent and independent variables (n=7693)

Variable	Description	Mean	Std. Dev.
SalePrice	Sale price of the property	576,450	328,812
PropertyType	Type of property (1=house, 0=unit)	72%	0.4
Bedrooms	Number of bedrooms	3	1
Baths	Number of bathrooms	2	1
Parking	Number of parking spaces	2	1
Amenities	Number of common destinations within walking distance (400 meters) of the property	2	5
DBRT	Street network distance to the nearest BRT stations (100's meters)	37.3	18.5
DTrain	Street network distance to the nearest Train (100's meters)	24.7	19.1
PopDensity	Population density (1,000's persons)	3.7	3.6
Older	Percentage of older people (aged older than 55 years) of the statistical area where the property located	10%	5%
HHincome	Median weekly household income of the statistical area where the property located	1,661	493
Hwy100m	Property located within 100 meters of a major road (1=yes)	2%	13%
DCBD	Euclidean distance from the property to the CBD (1,000's meters)	4.8	4.9
DRiver	Euclidean distance from the property to the river (1,000's meters)	2.6	2.5

5. Model Results and Discussion

A standard hedonic price model was first estimated using OLS. After the OLS estimation, the Breusch-Pagan test and Moran's I test were used to detect the presence of heteroskedasticity and spatial dependence. Both tests are highly significant ($p<.001$), indicating the existence of heteroskedasticity and strong spatial autocorrelation of the residuals.A spatial lag and a spatial error model were, therefore, employed to account for the spatial dependence. The model results of the three models are reported in Table 2.In the spatial lag model, the highly significant value of the *rho* coefficient, measuring the average influence of observations to their nearby observations, reflects the spatial dependence inherent in the data.In the spatial error model, the *lambda* coefficient is positive and highly significant, suggesting spatially correlated errors. Although some problems clearly remain, the two spatial models improved model fit, as indicated in higher R-squared and smaller AIC.

The coefficients of the independent variables among the three models appear relatively stable. For accessibility to BRT, a negative coefficient is expected since it is anticipated that being closer to the BRT would be associated with higher valuations of accessibility. This is indeed the case and, all else being equal, for every hundred meters closer to the BRT station, the housing price increases by 0.13percent, which is equivalent to $749at the mean of the data.However, access to the train station is negatively associated with housing price, with an about 0.15 percent decrease in housing price for every hundred meter closer to the train station.This may be accounted for by the poor level of service of trains in Brisbane as discussed in Section 3.1 above. Previous studies that have empirically investigated the impact of train station on property values have confirmed it has mixed effects on value of nearby properties (Bowes et al 2001). Stations may raise the value by reducing commuting cost or by attracting retail activity (Bowes et al 2001, Lee 1973 and Gatzlaff and Smith 1993). The negative effects may result from station noise, unsightliness and/or crime (Nelson and McCleskey 1990 and Nelson 1992)As expected, houses have a positive premium over aunit or apartment giving an outcome in line with Zhang (2010). More bedrooms, bathrooms, and parking are associated with a higher housing price in common with other studies using hedonic modelling. As described above, the socio-economics of the area and the neighbourhood environment also matter in determining the housing price. Higher population density, higher percentages of older people and higher median household income of the neighbourhood are associated with higher housing prices. In contrast, being located within 100 meters of a major highway reduces the housing price, probably because of the environmental nuisance(e.g., noiseand fuel emissions) of being close to roadways. Finally, all else being equal, a 1-km distance from the both the CBD and the river is associated with 1.7% and 4.6% decreases in housing price, respectively.

Table 2Results of the global models

	OLS			Spatial Lag			Spatial Error		
	Coef.	t		Coef.	t		Coef.	t	
DBRT	-0.0014	-9.05	***	-0.0014	-9.57	***	-0.0013	-4.60	***
DTrain	0.0015	8.24	***	0.0011	6.06	***	0.0018	5.70	***
PropertyType	0.1752	22.38	***	0.1568	20.89	***	0.2117	26.99	***
Bedrooms	0.1439	34.35	***	0.1339	33.71	***	0.1399	35.94	***
Baths	0.1456	30.71	***	0.1379	30.84	***	0.1294	29.11	***
Parking	0.0628	16.25	***	0.0613	16.83	***	0.0609	17.24	***
Amenities	0.0022	3.53	***	0.0029	4.86	***	0.0021	2.11	**
PopDen	0.0034	4.10	***	0.0042	5.42	***	0.0019	1.81	*
Older	0.7150	13.29	***	0.4994	9.77	***	0.5967	9.16	***
HHincome	0.0002	36.28	***	0.0001	19.00	***	0.0002	22.85	***
Hwy100m	-0.0639	-3.08	***	-0.0416	-2.13	**	-0.0359	-1.59	
DCBD	-0.0173	-25.18	***	-0.0115	-16.83	***	-0.0189	-15.74	***
DRiver	-0.0459	-29.35	***	-0.0387	-25.73	***	-0.0487	-18.11	***
Constant	11.9937	774.89	***	7.8926	55.01	***	12.0945	552.24	***
Lambda/Rho Coefficient				0.3275	28.73	***	0.4912	32.92	***
Number of obs.	7693			7693			7693		
R-squared	0.70			0.73			0.75		
Akaike info criterion	-458.74			-1223.39			-1373.61		

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

The Breusch-Pagan test and Moran's I test confirmed that the two spatial models helped to eliminate the spatial autocorrelation, as indicated by the Moran's I values (0.058 for spatial lag, -0.019 for spatial error, versus. 0.219 for OLS). But, asthe Breusch-Pagan test was significant for both spatial models this suggests the existence of spatial heteroskedasticity (i.e. spatial non-stationarity).

A GWR model was then used to directly model spatial variability.The model results indicated the GWR model was an improvement over the two spatial models, as indicated by the smaller AIC (-1590.83 as compared to -1223.39 and -1373.61). But this improvement in model fit needs to be set against a poorer performance in controlling for spatial autocorrelation with the GWR model being inferior to the two spatial models, as demonstrated by the greater Moran's I statistics (0.142).

Using the diagnostic approach described in Wheeler (2007), condition indexes and variance proportions to detect the potential collinearity problem for local models were calculated.The results indicated the condition number being greater than 30 at nearly half of the estimation points and a variance proportion beinggreater than 0.5 for several variables, indicating the presence of local collinearity according to Belsley (1991).This suggests that a GWR ridge regression might be more successful in reducing the estimation bias caused by local collinearity. A summary of the GWR Ridge model estimation results is presented in Table 3.The mean of the coefficients for all the variables have the same sign as the coefficients estimated from the global models although the magnitudes of the coefficientschanged in some places.

Table 3Summary of GWR local model estimations

Variable	Mean	Std. Dev.	Min	Max
DBRT	-0.0007	0.0013	-0.0031	0.0020
DTrain	0.0022	0.0022	-0.0024	0.0055
PropertyType	0.1775	0.0383	0.1149	0.2623
Bedrooms	0.1493	0.0231	0.1135	0.1890
Baths	0.1341	0.0134	0.1073	0.1590
Parking	0.0804	0.0297	0.0372	0.1520
Amenities	0.0031	0.0023	-0.0014	0.0094
PopDen	0.0003	0.0093	-0.0237	0.0276
Older	0.7490	0.2095	0.2137	1.1702
HHincome	0.0002	0.0000	0.0001	0.0003
Hwy100m	-0.0799	0.0385	-0.1572	-0.0182
DCBD	-0.0103	0.0296	-0.0512	0.0763
DRiver	-0.0001	0.0001	-0.0002	0.0000
Constant	12.0037	0.1113	11.8149	12.2142

As discussed in the Methodology, the other advantage of GWR is the visualisation of the local coefficients in a map. Figure 3illustrates the spatial variability of accessibility to BRT station on housing prices. This map shows values for accessibility which are significant with areas where the local parameters are insignificant being coloured light grey. In general, most parts of the study showthe expected negative relationship between access to the BRT station and housing price. It is also evident that this effectis relatively stronger at stations further away from the CBD withnon-significanteffects for some BRT stations closer to the CBD.These results align well with the findings of Bowes and Ihlanfeldt (2001) and Ma et al. (2014). But these outcomes could be expected because more travel time can be saved through use of the BRT by residents living farther away from the CBD. In addition, the accessibility of the BRT stations have both positive effects (e.g. accessibility, attracting retail activities) and negative effects (e.g. noise, crime near a station). In areas closer to the CBD, the benefits of access to BRT stations may be offset by the nuisances generated by proximity to the busway corridor or the neighbouring freeway.In the northern suburbs, the association between access to the BRT station and housing price is also negative, suggesting that nuisance there more than offsets the benefits. It is also possible that this result follows from the way in which train is preferred by residents living in these northern suburbs and this is somewhat confirmed by investigating the local estimates of distance to the train station in Figure 4.

By contrast, Figure 4 shows the unexpected negative association between access to the train station and housing price throughout most of the study area. This is consistent with the findings from the global models discussed above. Further, the strongest impact was at the train stations located close to the CBD:this is possibly because the benefits of access to a train station is small in terms of accessibility and total time savings while the negative effects (e.g. noise, crime, pollution) might be higher.Figure 3 also shows the negative effects declining as the distance from the CBD to the southern suburbs increased (i.e. the coefficients becoming less positive) This suggests the increased accessibility benefits of being close to a train station as houses become more suburban may offset some of the negative effects observed closer to the CBD but these not being strong enough to overturn the overall negative effect. The way in which this study has identified unexpected negative associations between access to train stations and housing prices is not unique. For example, Cervero and Duncan (2002) found that commuter rail had a negative effects on the sales price of multi-family properties in their San Diego County study with only one area – the northern suburbs – showing a positive association between access to the train station and housing price. Whilst the accessibility benefits not being able to offset the negative aspects of being close to a train station is one explanation it is also possible that other local factors, not controlled in the modelling, are affecting the capitalization effects of being close to a train station. In this context, in the northern part of the study area there are several train routes (see Figure 1) which combined will provide a more frequent services and larger coverage: both factors are key determinants of capitalization effects(Landis et al., 1994).

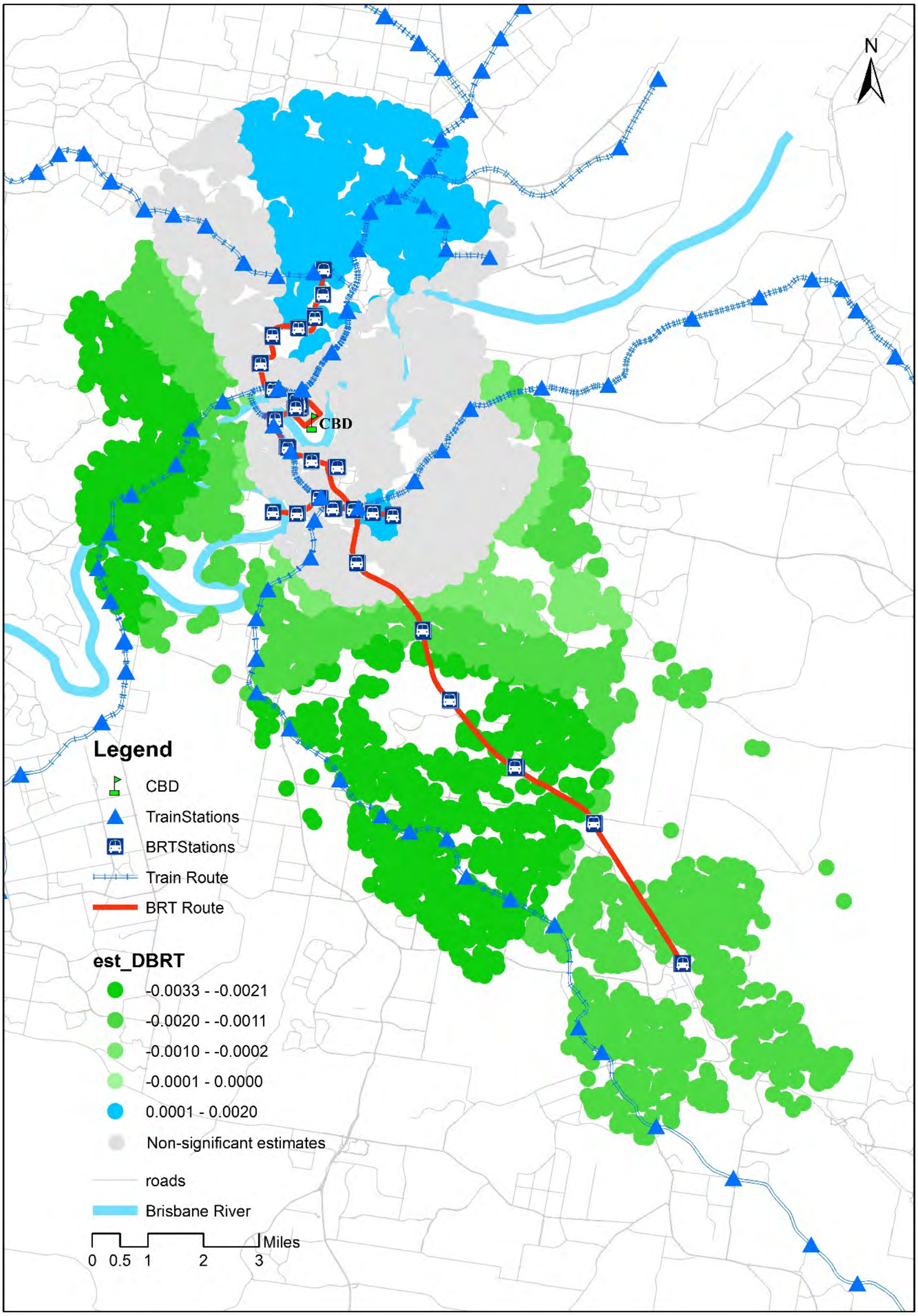

Figure 3 Local estimates of distance to the BRT station

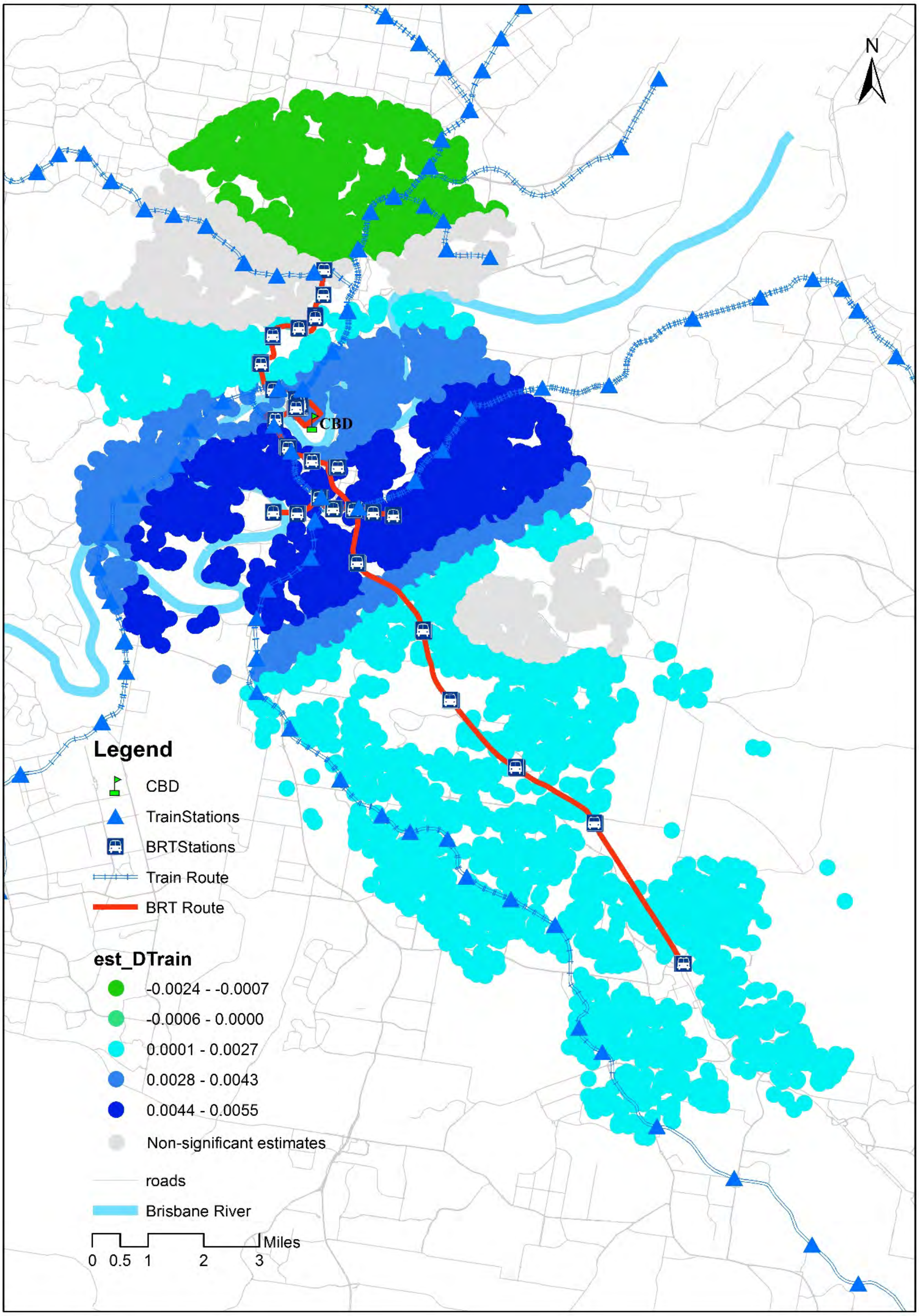

Figure 4 Local estimates of distance to the train station

6. Conclusion and Policy Implications

This study quantitatively evaluates the direct accessibility valuation of proximity of residential property to the BRT in Brisbane, Australia. Results from global models, OLS and spatial models, consistentlysuggestthat, everything else held constant, being close to BRT adds a premium to the housing price of 0.14%,for every hundred meters closer to the BRT station or 0.36% for every 250m closer to the BRT station which is somewhat lower than the 2.4% uplift found by the meta-analysis of Debrezion et al. (2007) for a similar proximity to a railway station.Results from the GWR local model further indicated that proximity effects vary over space. In general, the proximity effects are relatively stronger at stations further away from the CBD, indicating people living in suburbs are more likely to pay extra for being close to a BRT station. However, this is not consistent throughout the study area suggesting that some unique local characteristics have not been controlled in models and appear to moderate the relationship between proximity to BRT station and housing price. For example, in the northern suburbs of the study area, there was a negative premium for proximity to the BRT station but the opposite for proximity to train station. The GWR local model showed this variability in the maps and suggests that further investigations of the local factors contributing to the variations of the proximity effects could be beneficial. Thisresult is important not only for better understanding the implications of BRT proximity effects on property price, but for policy implications in being able to capture the uplift in land value. The implementation of new BRT systems in developed countries might surmise from this that the uplift is lower than rail systems, but so is the capital expenditure. The fact that uplift is lower, is not necessarily a bad outcome.

It is also worth noting that the areas with high premia on house prices are served by the BUZ routes which provide extensive feeder buses and very high frequency. This shows the importance of frequency to passengers. These services, unlike their counterparts in developing countries, traverse the suburbs and then operate directly onto the Busway providing single seat journeys without interchange at the busway for journeys into the CBD.Relying on the feeder bus network, the BRT system in Brisbane argues that this significantly expands its service areaand is one of the key factors contributing to the significant and widespread capitalization effects. The choice of an open BRT system (as in Brisbane) or a closed BRT system (as in many developing countries) also needs to be considered in the design of a BRT system. The crucial difference is the degree of interchange and closed systems relay heavily on frequent services to minimise interchange delay and the removal of a financial interchange penalty.

By comparing the results of different models, the spatial models fit the data better than OLS model by taking account of spatial effects. The spatial error model was the best in handling the spatial autocorrelation problem. The OLS estimation results are, however, stillunbiased even in the presence of spatial dependence effects, as shown by the similar results from OLS and spatial models.The GWR local model improves the spatial models by further accounting for the spatial non-nonstationarity, but introduces the challenge of local collinearity. The empirical research using the GWR model to investigate the spatial effects on property values is limited, further studies are needed to better understand the factors contributing to the spatial effects.

7. References

Australian Bureau of Statistics, 2015. Regional Population Growth, Australia, 2013-14, 31 March 2015 ed.

Bárcena, M., Menéndez, P., Palacios, M., Tusell, F., 2014. Alleviating the effect of collinearity in geographically weighted regression. J. Geograph. Systems 16, 441-466.

Belsley, D.A., 1991. Conditioning Diagnostics: Collinearity and Weak Data in Regression. John Wiley and Sons, New York.

Billings, S.B., 2011. Estimating the value of a new transit option. Reg. Sci. Urban Econ. 41, 525-536.

BITRE, 2012. Urban Public Transport Patronage estimates. Bureau of Infrastructure, Transport and Regional Economics, Canberra, Australia.

BITRE, 2013. Urban Public Transport Patronage estimates. Bureau of Infrastructure, Transport and Regional Economics, Canberra, Australia.

BITRE, 2014. Urban Public Transport Patronage estimates. Bureau of Infrastructure, Transport and Regional Economics, Canberra, Australia.

Bowes, D.R., Ihlanfeldt, K.R., 2001. Identifying the impacts of rail transit stations on residential property values. J. Urban Econ. 50, 1-25.

Cervero, R., Duncan, M., 2002. Land Value Impact of Rail Transit Services in San Diego County. Report prepared for National Association of Realtors Urban Land Institute, Washington, D.C.

Cervero, R., Kang, C.D., 2011. Bus rapid transit impacts on land uses and land values in Seoul, Korea. Transp. Policy 18, 102-116.

Cosgrove, D.C., 2011. Long-term patterns of Australian public transport use, 34th Australasian Transport Research Forum (ATRF), Adelaide, Australia.

Debrezion, G., Pels, E., Rietveld, P., 2007. The impact of railway stations on residential and commercial property value: a meta-analysis. The Journal of Real Estate Finance and Economics 35, 161-180.

Deng, T., Nelson, J.D., 2010. The impact of bus rapid transit on land development: a case study of Beijing, China. World Academy of Science, Engineering and Technology 66, 1196-1206.

Devney, J., 2014. Redesigning bus networks to be simpler, faster and more connected, Australian Institute of Traffic Planning and Management (AITPM) National Conference, 2014, Adelaide, South Australia, Australia.

Dubé, J., Des Rosiers, F., Thériault, M., Dib, P., 2011. Economic impact of a supply change in mass transit in urban areas: a Canadian example. Transportation Research Part A: Policy and Practice 45, 46-62.

Fotheringham, A.S., Brunsdon, C., Charlton, M., 2003. Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons.

Gatzlaff, D.H. and M.T. Smith, 1993. The impact of the Miami Metrorail on the value of residences near station locations. Land Economics,69(1), 54-66.

Gollini, I., Lu, B., Charlton, M., Brunsdon, C., Harris, P., 2013. GWmodel: an R package for exploring spatial heterogeneity using geographically weighted models. arXiv preprint arXiv:1306.0413.

Hoerl, A.E., Kennard, R.W., 1970. Ridge regression: Biased estimation for nonorthogonal problems. Technometrics 12, 55-67.

Hoffman, A., 2008. Advanced Network Planning for Bus Rapid Transit: The "Quickway" Model as a Modal Alternative to "Light Rail Lite". Federal Transit Administration, USDOT, Washington, DC.

Jun, M.-J., 2012. Redistributive effects of bus rapid transit (BRT) on development patterns and property values in Seoul, Korea. Transp. Policy 19, 85-92.

Knight, R.L., Trygg, L.L., 1977. Evidence of land use impacts of rapid transit systems. Transportation 6, 231-247.

Lancaster, K.J., 1966. A new approach to consumer theory. The journal of political economy, 132-157.

Landis, J., Guhathakurta, S., Zhang, M., 1994. Capitalization of transit investments into single-family home prices: A comparative analysis of five California rail transit systems. University of California Transportation Center.

Lee, D. 1973. Case studies and impacts of BART on prices of single family residences. University of California, Institute of Urban and Regional Development, Berkeley, CA,.

Ma, L., Ye, R., Titheridge, H., 2014. Capitalization effects of rail transit and bus rapid transit on residential property values in a booming economy. Transp. Res. Rec. 2451, 139-148.

Mulley, C., 2014. Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. Urban Stud. 51, 1707-1724.

Munoz-Raskin, R., 2010. Walking accessibility to bus rapid transit: Does it affect property values? The case of Bogotá, Colombia. Transp. Policy 17, 72-84.

Nakaya, T., 2001. Local spatial interaction modelling based on the geographically weighted regression approach. GeoJournal 53, 347-358.

Neelagama, I., 2014. Rapid Transit Investing in Australia's Transport Future. Bus Industry Confederation, Kingston ACT.

Nelson, A.C. and S.J. McCleskey, 1990. Improving the effects of elevated transit stations on neighborhoods. Transportation Research Record, 1266, 173-180.

Nelson, A.C.,1992. Effects of elevated heavy-rail transit stations on house prices with respect to neighborhood income. Transportation Research Record, 1359, .127-132

Perk, V.A., Catala, M., 2009. Land use impacts of bus rapid transit: effects of BRT station proximity on property values along the Pittsburgh Martin Luther King, Jr. East Busway. Federal Transit Administration.

Queensland Government, 2012. Travel in south-east Queensland.

Ricardo, D., 1821. On the principles of political economy and taxation.

RICS, P.U., 2002. Land value and public transport: stage 1-summary of findings. UK: Office of the Deputy Prime Minister.

Rodríguez, D.A., Mojica, C.H., 2009. Capitalization of BRT network expansions effects into prices of non-expansion areas. Transportation Research Part A: Policy and Practice 43, 560-571.

Rodríguez, D.A., Targa, F., 2004. Value of accessibility to Bogotá's bus rapid transit system. Transport Reviews 24, 587-610.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. The journal of political economy, 34-55.

Salon, D., Shewmake, S., 2011. Opportunities for value capture to fund public transport: A comprehensive review of the literature with a focus on East Asia. Available at SSRN 1753302.

Smith, J.J., Gihring, T.A., 2006. Financing transit systems through value capture. Amer. J. Econ. Sociology 65, 751-786.

Smith, J.J., Gihring, T.A., Litman, T., 2009. Financing transit systems through value capture: an annotated bibliography. Victoria Transport Policy Institute, Canada.

Soltani, A., Tanko, M., Burke, M.I., Farid, R., 2015. Travel Patterns of Urban Linear Ferry Passengers: Analysis of Smart Card Fare Data for Brisbane, Australia, Transportation Research Board 94th Annual Meeting.

Trivelli, C., 1997. Agricultural land prices. SDdimensions online publication of the Food and Agriculture Organization of the United Nations.

Vuchic, V.R., 2007. Urban Transit Systems and Technology, p. 602p.

Wheeler, D., Tiefelsdorf, M., 2005. Multicollinearity and correlation among local regression coefficients in geographically weighted regression. J. Geograph. Systems 7, 161-187.

Wheeler, D.C., 2007. Diagnostic tools and a remedial method for collinearity in geographically weighted regression. Environ. Planning A 39, 2464-2481.

Wheeler, D.C., Waller, L.A., 2009. Comparing spatially varying coefficient models: a case study examining violent crime rates and their relationships to alcohol outlets and illegal drug arrests. J. Geograph. Systems 11, 1-22.

Zhang, M., 2009. Bus versus Rail: Meta-analysis of cost characteristics, carrying capacities, and land use impacts. Transp. Res. Rec. 2110, 87-95.