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The South Eastern BRT Network in Brisbane, Australia: How much is added to residential house values as a result of the network effect?

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ABSTRACT: This paper addresses an area of policy much understudied in the literature. It emerged out of investigating the policy needs of governments seeking to find new ways of funding public transport infrastructure. Land rent theory (Alonso, 1964) identifies that the value of unimproved land reflects accessibility gradients with new transport infrastructure, through improvements in accessibility, uplifting land values. Capturing the uplift in land value for funding requires that the amount of uplift be known as well as when the uplift occurs – is this after the announcement of the project, after building starts or when the new infrastructure starts to operate?

However, many cities plan a number of projects over a longer timescale, what is the value of the network effect as additional infrastructure provides the opportunity to access more destinations quickly. This network effect is a case of a 'product' that has less value in isolation but increases in value when in combination with other 'products' (Katz and Shapiro, 1994).

There have been a few studies on the timing of uplift (Gatzlaff and Smith, 1993; Knaap et al., 2001), but these have been generally confined to rail based infrastructure in the public transport domain. The objective of this paper is to identify how much is added to residential land values through the provision of bus rapid transit (BRT) in Brisbane, Australia and to identify specifically the value of the network effect as incrementally adding to existing transport infrastructure as a feature of Australian cities.

The paper is structured as follows. The next section explores the literature context for this study. This is followed by a description of the data and the case-study area. The method follows which describes the difference in difference methodology employed while the following section interprets the results. The final section discusses the results and concludes with recommendations for future research.

KEY WORDS: ***BRT, network effect, value uplift, difference in differences modelling***

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1. Introduction

This paper addresses an area of policy much understudied in the literature. It emerged out of investigating the policy needs of governments seeking to find new ways of funding public transport infrastructure. Land rent theory (Alonso, 1964) identifies that the value of unimproved land reflects accessibility gradients with new transport infrastructure, through improvements in accessibility, uplifting land values. Capturing the uplift in land value for funding requires that the amount of uplift be known as well as when the uplift occurs – is this after the announcement of the project, after building starts or when the new infrastructure starts to operate?

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2. Literature Context

When does uplift to land from transport infrastructure occur? This is likely to depend on the type of property or land and the context of the infrastructure improvement. For commercial land, land values could rise from announcement as entrepreneurs internalise the proposed accessibility into development activity. Also, identifying the impact for commercial land is often easier as new developments need to go the planning frameworks in which planning gain is typically identified and extracted. For residential land, the position is less clear with previous studies providing results showing uplift at different times. For this case study, a previous study has identified the long term land value uplift associated with the BRT (Mulley et al., 2016) and so it is expected that an uplift will be identified but no a priori prediction as to when this will have been delivered (post-announcement, the building phase or post-operation).

Loomis et al. (2012) found that a new heavy rail transit system in San Juan, Puerto Rico did not have any significant impacts on land values until the new service was operational. Loomis et al. suggested that this delay could be caused by citizens having limited confidence in the government agency responsible for delivering the project. Against this, studies by McDonald and Osuji (1995) and McMillen and McDonald (2004) suggest that value uplift can be anticipated by the market in advance of implementation. A recent study in Australia (Mulley and Tsai, 2016) suggests that uplift in Sydney occurred shortly after opening but with no significant uplift in the relatively short period between announcement, building and opening. This paper also pointed to potential trust issues in terms of implementation since the government had a record of announcing and cancelling projects.

Apart from specific timing issues, the empirical work demonstrates that there is no reason to believe that uplift will occur linearly from the base values to the uplifted values. For a new road Chernobai et al. (2011) used a spline regression model and found that land values of residences increased in the early part of the construction period and for a short period after opening but only for locations that were up to 0.64km (0.4 miles) from the freeway. Mixed results were found by Golub et al. (2012) for the new light rail line in Phoenix, Arizona, with land values increasing throughout the announcement and building phases but this contrasts with Knaap et al. (2001) who looked at vacant residential lots and found these increased in the majority of places immediately after announcement but then fell in the following year. There are also some criticisms of studies that use pooled data rather than true panel data, such as the study by Gatzlaff and Smith (1993) as this creates the possibility that uplift in one period may obscure uplift in another period (Loomis et al., 2012).

As Rodrigues and Mojica (2009) identify, the network effect has been poorly studied in terms of the capitalisation of the network effect impact into property prices, despite the way in which network additions are perhaps a more frequent occurrence than totally new networks (Garrison and Levinson, 2006 as cited by Rodriguez and Mojica) and complementary to existing services thus providing positive externalities to those residents of properties accessible to the existing services (Economides, 1996). This is the particular focus of this study.

Longitudinal data, and preferably true panel data, is required to investigate timing issues and to identify whether planners site BRT stations where the uplift is happening or whether uplift happens as a result of the siting of the BRT station Rodríguez and Mojica (2009). Whilst it is always preferable to have true panel data to determine when the uplift occurs, practicalities have determined that longitudinal data is more often used. For example, repeat sales data is often used to match data before and after implementation of infrastructure (McMillen and McDonald (2004) but often this does not provide sufficient variablity or sufficient quantity of data (Mulley and Tsai, 2016). This paper uses a form of repeated cross-section data to address this issue using a methodology that provides a causal link between when the infrastructure is implemented and the uplift in land that is associated with it.

In summary, the study of when the uplift to property value arises as a result of new transport infrastructure is under-reported in the literature. More importantly, the additional value to properties as a result of the network effect is rarely studied. This study uses longitudinal data to examine when the uplift to properties close to the South Eastern busway in Brisbane, Queensland become capitalised into house prices and separately how large an uplift is created by the positive externalities of extensions to the BRT elsewhere in Brisbane for the residents close to the South Eastern busway.

3. Data and 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 of the plot, number of bedrooms, bathrooms and parking places, and latitude/longitude of the property. As this paper is primarily concerned with the timing of the effects of BRT on property values, all properties sold in 1996, 2002, 2006, and 2011 in Brisbane were used for this longitudinal analysis. The transaction data was chosen to match with the census data, which provides the best data for neighbourhood effects. Exploratory analysis identified that the impacts of transport infrastructure on house and unit or

apartments are different in this study area. Houses and apartments have been confirmed as different in other studies for Australia (Mulley, 2014; Tsai et al., 2016) and also in other countries (Billings;2011, Cervero and Duncan, 2002, Cervero and Kang (2011). Where much larger datasets have been available, distinguishing betweeen a greater number of property types is possible, with many being confirmed as having signficantly different uplifts from the same infrastructure (Debrezion et al., 2011). For simplicity, this study only considers house properties.
The properties were geocoded in GIS using the coordinate information. 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*) was measured to indicate the regional location characteristic of the property. Further, the census data of year 2002, 2006 and 2011, collected at SA2 level (the smallest geography available for this longitudinal data), were spatially joined by the properties to acquire the neighbourhood characteristics including population density (*PopDen*), percentage of older people (*Older*), percentage of English only speaking people (*English*), percentage of population with college and higher qualification (*College*), percentage of indigenous population (Indigenous), percentage of unemployed population (*UnEmp*), and median weekly household income (*HHincome*). In between 1996 and 2002 there was a change in the geography for the census data in Australia and an exactly comparable dataset was not available. Data for 1996 was created by imputing the average increase/decrease in demographic composition from year 2002 to 2011. The descriptive analysis of the variables is provided in Table 1.

Table 1 Descriptive analysis

	year 1996 (n=13,548)		year 2002 (n=26,720)		year 2006 (n=18,382)		year 2011 (n=11,535)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sale price	171,956	99,462	281,159	185,471	461,257	298,794	600,587	332,945
Distance to South Eastern busway stations (metres)	-	-	8025.1	5336.7	8420.7	5385.1	8594.0	5337.2
Distance to CBD (kilometres)	11.0	5.3	11.4	5.5	11.8	5.5	11.5	5.3
Distance to train stations (kilometres)	3.2	2.4	3.5	2.7	3.6	2.9	3.5	2.8
Land area (1000 sqm)	1.1	3.7	1.1	4.4	1.0	8.7	1.0	3.2
% Older	20%	7%	20%	5%	22%	5%	22%	4%
% English speaking only	86%	8%	82%	9%	80%	10%	78%	12%
% Indigenous	1%	1%	1%	1%	1%	1%	1%	1%
% Married	39%	7%	39%	6%	38%	6%	38%	6%
% Unemployed	8%	2%	7%	2%	4%	1%	5%	2%
% College	11%	7%	15%	7%	18%	7%	22%	8%
Population density (persons/sqkm)	1606	731	1685	854	1773	889	1910	923
Median household income (AU$ per week)	692	324	911	199	1220	244	1615	345

Brisbane's 32km busway network services the inner and middle suburbs of Brisbane. Most services are focussed on the CBD but there are also significant cross-suburban services to the University of Queensland. Under Vuchic's (2007) definitions, the Brisbane busways are almost entirely Category A i.e. running on dedicated roadway which is provided with fully segregated and physically protected rights-of-way. This includes significant grade separation both above the surface on the street network, particularly along the South Eastern Busway, and large underground sections in the CBD and inner city. For only around 400m total and three intersections in South Brisbane and at North Quay does the BRT system revert to bus-lanes which interface with other traffic.

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-routed to the city centre with almost no feeder buses, although significant numbers of passengers interchange at busway stations for services, especially to the University of Queensland. This planning of routes to continue to destinations in suburbs away from the dedicated structure contrasts with the network structure of successful South American BRT using a closed system design of services running on the infrastructure with interchange to reach neighbourhoods not on the infrastructure..

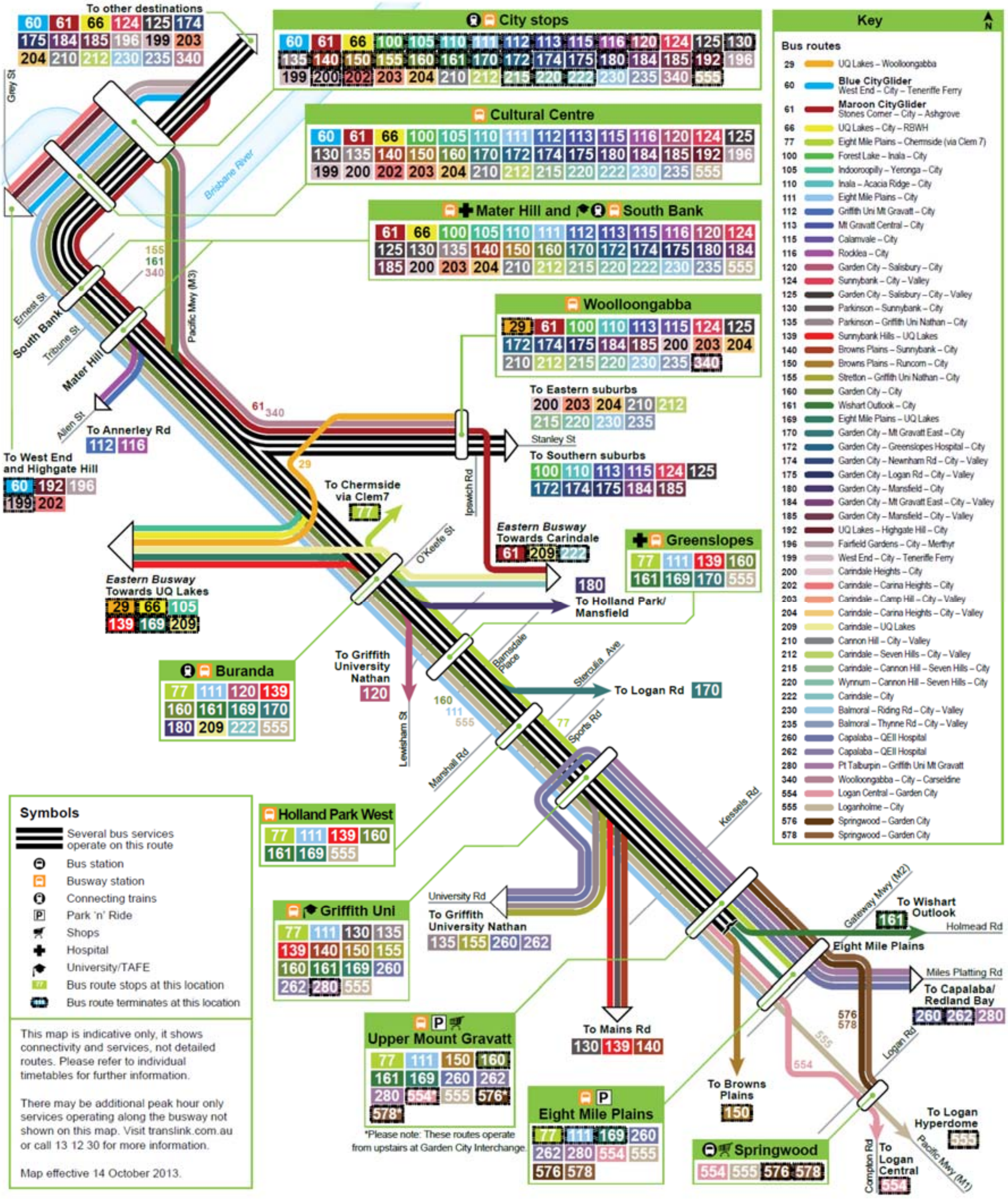
The system in Brisbane is relatively mature, with the first sections opened in the year 2000. Over 300 buses per hour now travel on key links of the South Eastern Busway in 2007, carrying over 20,000 passengers per hour in the peak, not far from the theoretical limit of BRT operations. The system carries 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. This study is concerned primarily with the South Eastern Busway network. However it is recognised that over the study years, different parts of the Brisbane Busway network were announced and constructed, thus providing an ever increasing network as opportunities for travel for residents with access to the South Eastern network. Figure 1 shows the South Eastern Busway network as of 2013.

The Brisbane busway stations were announced, constructed and opened in different years (Table 2). The majority of South Eastern Busway was opened before 2002. The longitudinal data of this study allows for the impact of the network effect to be explored for South Eastern Busway. The network effect arises from the way in which all three busway lines are connected so riders of South Eastern Busway benefit from the opening of Northern and Eastern Busways to access a wider set of destinations quickly, thus adding additional uplift to properties close to the South Eastern Busway stations.

Table 2 Timing of busway stations in Brisbane

	Announcement	*Construction*	*Open*
South Eastern Busway			
City - Woolloongabba	Aug-96	Sep-98	Sep-00
Woolloongabba - Eight Mile Plains	Aug-96	Nov-98	Apr-01
Eight Mile Plains - Springwood Station Stage I	Jun-10	Dec-12	Aug-14
Eight Mile Plains - Springwood Station Stage II	Jan-02	Mar-02	Sep-03
Northern Busway			
QUT Kelvin Grove	Jan-99	Sep-02	Feb-04
Normanby; RCH Herston	Jan-99	Apr-00	Dec-05
King George; Roma street	Jan-99	Jul-06	May-08
Herston to Windsor	May-07	Aug-08	Aug-09
Windsor to Kedron	May-07	Oct-08	Jun-12
Eastern Busway			
UQ Lakes and the South Eastern Busway	Aug-05	May-06	Aug-09
Buranda to Main Avenue	Jun-08	Aug-09	Aug-11

Sources: Queensland Government, Department of Transport and Main Roads



Source: TRANSLink, Queensland Governments

Figure 1 South Eastern Busway network map

4. Method

The objective of this paper is to evaluate the incremental effects of accessibility to a busway network on property values of houses over time. Difference-in-differences (DD) models are employed to explore whether there are significant differences between the treatment group (properties close to busway stations) and the control group (properties not close to the busway stations) in terms of housing price changes (first difference), before and after the opening of busway stations (second difference). DD models for estimating the effect of policy implementation have become very popular in economics and other social sciences (Athey and Imbens, 2002). DD estimation works by comparing the difference in outcomes before and after the intervention for groups affected by the change (the treatment group) to this difference for unaffected groups (the control group) (Bertrand et al., 2002). DD models control for all time-invariant unit-level factors which may not be observable or measureable but can lead to omitted variable bias (Card and Krueger, 1993). DD estimation is also attractive because of its simplicity on the one hand and, on the other hand, its potential to avoid many of the endogeneity problems that typically arise in OLS regression (Bertrand et al., 2002). The DD model is specified as:

$$\ln(p_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 N_{it} + \beta_3 BRT_{it} + \sum \beta_t year_{it} + \sum \theta_t BRT_{it} * year_{it} + \sum_{j=1}^{12} \delta_j D_{ij} + \epsilon_{it} \quad (1)$$

Where, p_{it} represents the transaction price for housing unit *i* at time point *t (t=1996, 2002, 2006, 2011)*. β_0 is the constant (and a combination of reference values, given the several fixed effects in the model and the control variables). X_{it} is a vector of structural characteristics for property *i* in year *t*; N_{it} is a vector of neighbourhood characteristics for property *i* in period *t*; BRT_{it} is an indicator variable that takes value equal to 1 if the property *i* belonging to South Eastern busway service area in year *t*, and 0 otherwise; $year_{it}$ is an indicator variable that takes value equal to 1 if the property *i* was sold in year t; D_{ij} =1 if property *i* sold in month j (j=1, 2, …, 12), and equals 0 otherwise; and ϵ_{it} is the error term for property *i* in year *t*. The term $\sum \beta_t year_{it}$ controls for general increases in price due to inflation whereas $\sum_{j=1}^{12} \delta_j D_{ij}$ controls for seasonal variation. The interaction of BRT_{it} and $year_{it}$is our difference-in-difference estimator, which tests whether there is a difference in housing price change over year between the properties located within the busway service area (*treatment*) and those not (*control*), after the open of South Eastern Busway, and thus θ_t is the coefficient of interest.

Two methods to define the treatment and control groups were employed. First, similar to many previous studies, we define the treatment group as the properties located within 800m of busway stations, while those located beyond 800m but within 1600m of busway stations are identified as the control group. This method is based on the assumption that most of busway riders will not walk more than 800 meters to a station, and that the properties within 800m of busway stations are similar to those located between 800-1600m of busway stations. While the 800m has been widely accepted as the cut-off distance of accessing to a bus stop (Daniels and Mulley, 2013; Seneviratne, 1985), the latter assumption on similar properties within and beyond 800m is not guaranteed and this hypothesis is not formally tested. In any case, it is not clear what characteristics of a property need to be ‘similar’ in order to formally test between houses in a treatment and control area and this has therefore remained somewhat of an ‘art’ rather than science. Without a comparable treatment and control group, the effects of accessibility to public transport infrastructure on property values is biased and so the choice of control area is of great importance.

A second approach to choosing the control group was chosen primarily to reduce the bias resulting from the differences between the treatment and control groups, and to provide a more objective underpinning to the choice is through the use of propensity score matching. The treatment group is retained as the neighbourhoods located within 800m of the busway stations. For this the method adopted by Billings (2011)(Billings, 2011a) is used to conduct the propensity score matching. This involves first estimating a probit model using neighbourhood areas as the unit of analysis and to use this model to predict the probability of becoming a busway station. The dependent variable is an indicator variable for a neighbourhood being located within 800m of the busway stations with the independent variables including measures on various neighbourhood characteristics. In this study this included those described in Table 1 (e.g., *DCBD*, *PopDen*, *Older*, *HHIncome*). Following Billings (2011) a common support assumption is used in implementing the propensity score matching, and this restriction excluded any neighbourhood whose score is outside the range of possible propensity scores for either treatment or control groups. The estimation identified six blocks where the mean propensity score is the same for treated and control areas in each block. The final stage is to use the fitted values as the propensity score to match the treatment and control neighbourhoods. This approach therefore is more objective than simply using an area beyond a plausible catchment area as the control area. Figure 3 illustrates the differences in defining the treatment and control groups between the two approaches.

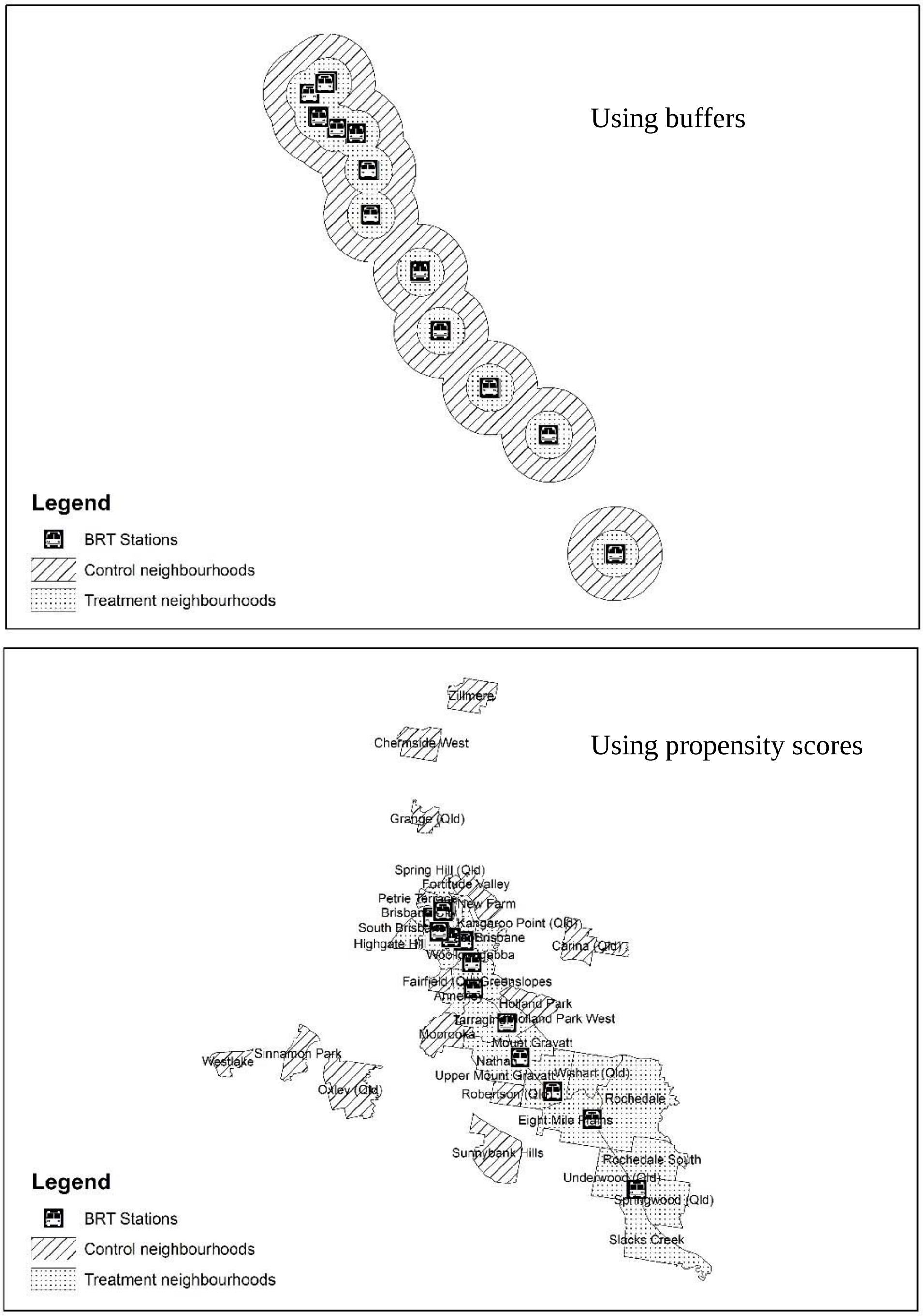


Figure 3 Different control areas using buffers or propensity scores

5. Results

As described in Method above, two approaches were used to identify the control areas. Consequently two models were estimated using each of the sets of treatment and control groups. The results are presented in Table 3. Overall, model fit is good for both models with approximately 70 per cent of the variation in the data being explained.

In the first model, the treatment group is all the properties that are located within 800m of a South Eastern Busway station with the control group is the properties that are located beyond 800m but within 1600m of a South Eastern Busway station. In the second model, the treatment area is still the properties within the neighbourhoods that are located within 800m of a South Eastern Busway station, and the control group is the properties within the matched control neighbourhoods, selected based on propensity score matching

Table 3 Model Results

	Model 1			**Model 2**		
	Coef.	t	P>t	Coef.	t	P>t
treatment	-0.07	-3.20	0.00	-0.13	-10.50	0.00
year						
2002	0.48	28.38	0.00	0.28	23.41	0.00
2006	0.99	36.10	0.00	0.63	36.04	0.00
2011	1.10	34.15	0.00	0.64	31.82	0.00
treatment x 2002	0.07	2.59	0.01	0.04	2.66	0.01
treatment x 2006	0.07	2.28	0.02	0.07	4.41	0.00
treatment x 2011	0.10	2.78	0.01	0.07	3.74	0.00
DCBD	-0.03	-14.71	0.00	-0.01	-8.10	0.00
Area	0.06	14.62	0.00	0.00	7.04	0.00
Dtrain	0.00	-0.86	0.39	0.02	11.61	0.00
Bedrooms	0.02	5.55	0.00	0.01	3.59	0.00
Baths	0.08	9.12	0.00	0.09	14.79	0.00
% older	-0.76	-6.82	0.00	-0.58	-8.00	0.00
% married	1.18	10.04	0.00	0.09	1.23	0.22
% unemployed	3.54	11.47	0.00	1.96	9.91	0.00
% college	1.04	6.53	0.00	3.62	40.76	0.00
February	0.04	2.15	0.03	0.04	3.10	0.00
March	0.06	3.12	0.00	0.04	3.49	0.00
April	0.07	3.30	0.00	0.05	4.22	0.00
May	0.05	2.51	0.01	0.05	3.98	0.00
June	0.08	3.61	0.00	0.05	3.85	0.00
July	0.07	3.58	0.00	0.06	5.04	0.00
August	0.10	4.60	0.00	0.08	6.40	0.00
September	0.08	3.98	0.00	0.07	5.28	0.00
October	0.13	6.07	0.00	0.10	7.45	0.00

November	0.12	6.02	0.00		0.11	8.82	0.00
December	0.12	5.57	0.00		0.11	8.42	0.00
constant	11.34	177.84	0.00		11.53	301.62	0.00
Number of obs	5716			Number of obs	15,397		
F(27, 5688)	480.12			F(27, 15369)	1268.27		
Prob > F	0.00			Prob > F	0.00		
R-squared	0.70			R-squared	0.69		
Adj R-squared	0.69			Adj R-squared	0.69		

In both models, the variables of interest are the interaction terms between treatment and year. These are the DD estimators and their coefficients are the estimated effects of busway stations on property values over the years, relative to 1996. As identified above, the majority of the South Eastern busway was announced (August 1996), constructed (start of 1998) and opened (2000-2001) in between the first observation of 1996 and 2002. As the busway is announced, built and opened by 2002, the increases in property prices shown by the DD estimators for this year and subsequent years take account of the impact of the network effect for these properties – enhanced accessibility to a wider range of destinations enabled by the presence of this busway and other busways opening in the area. The results for Model 1 show a positive impact of 7% on housing price for properties located within 800m of busway stations immediately after the opening of the South Eastern Busway, and this impact is still the same four years' later after the opening, even though two stations are opened on the Northern busway although not connected to the CBD directly. Compared to announcement in 1996, the South Eastern Busway created an increase of 10% by 2011 and, by this time the majority of the Northern Busway was complete and connected to the South Eastern Busway through tunnels traversing the CBD. In addition, the Eastern Busway was opened in 2011 but the network effect of this opening is unlikely to be fully captured in the 2011 data. Previous studies (Billings, 2011b; Knaap et al., 2001) have shown the capitalization effect is not instant but takes time. The network effect can be considered as the impact of the service area increasing which Landis et al. (1995) has shown increases property prices from BRT implementation. All this is against a background of increasing prices on average with the variable 2002 showing an average 48% increase over 1996, the variable 2006 showing a 99% increase over 1996 and the variable 2011 showing a 111% increase over 1996, having controlled for other effects in the model.

For the other independent variables in Model 1, the signs are as expected with the exception of the percentage of unemployed. Distance to the CBD and distance to rail stations have a negative relationship with price of houses showing increased accessibility to rail stations and closeness to the CBD increases property prices. An additional bedroom and bathroom adds 3 per cent and 8 per cent to house price respectively on average. As with other hedonic type modelling, the socio demographic and neighbourhood variables are significant.

In the second model, propensity score matching is used to identify control areas which match the treatment areas of the 800m buffer around busway stations. As identified above, the propensity score matching is likely to create a more robust control area and, to the extent that the results are different, more confidence can be attributed to the likely lack of bias in Model 2 results. Table 3 shows that Model 2 tells a different story in part. Here the interaction terms suggest that the uplift is complete by 2006 and does not rise any more by 2011, relative to 1996. This model therefore suggests that there was no network effect from the opening of the Northern and Eastern busways since this did not add to uplift for houses located close to the South Eastern busway. As with Model 1, distance to CBD and distance is of the expected sign but lower than in Model 1. Distance to train stations is the only variable where the coefficient is higher than in Model 1 at 2 per cent on average. Indeed all the other effects (timing and socio demographics) are significant and interpretable as identified above for Model 1 but smaller in absolute terms.

6. Discussion and Conclusions

This study explores the network effect of BRT effects on houses in Brisbane, Queensland. The models were also run both on units (apartments) separately and included in Models 1 and 2 with dummy variables denoting the apartments. However, both these approaches revealed that that units and houses behave quite differently as is discussed above where this is substantiated by other studies. It is suspected that the separate models for units did not work so well because of the way in which the analysis compared treatment and control areas. In both methods for identifying control areas, it is thought that units do not fare well. In Australian cities, units are a relatively new concept with the low density sprawl characterised by the house on the quarter acre block. Units are a more recent phenomenon and have been encouraged by land use policies associated with transport development. Thus for Model 1, it is unlikely that a control area beyond 800m will have units similar to that around busway stations. For Model 2, the explanation is less clear. However, it is the case that the neighbourhoods identified by propensity scoring are larger than the treatment areas and in these, finding appropriate controls for units which are built in response to the busway is not effective.

Of the methods used in this study to identify the control area the propensity score approach is more appropriate since it is an objective and defensible way of creating a control. Using a buffer is no guarantee that the control area will have similar properties or similar socio demographics. Having identified this, it is recognised that each method has advantages and disadvantages. The advantage of the buffer around the busway station approach is that a more constant sized area is created as the control. In contrast, the propensity score approach is based on neighbourhoods which sometimes are larger or smaller than the buffer around the busway station and only the average values for this area count in terms of comparability.

In both models, the DD interaction terms show increases in property prices due to better accessibility to busways themselves and through the network effect of access to a greater service area. This finding of this study is consistent with Rodríguez and Mojica (2009) who also found a positive impact of BRT network expansions on property values. Whilst previous studies have highlighted methodological differences and suggest these are responsibility for differences in identified uplift (for example the meta studies of Debrezion et al. (2007), Smith and Gihring (2006) and Smith et al. (2009). However, this study highlights a different concern relating to the way in which sampling and the choice of control can create different outcomes, despite the way in which the range of 10 per cent (Model 1) and 7 per cent (Model 2) for value uplift is well within the range of other studies (Cervero and Duncan, 2002; Debrezion et al., 2007; Landis et al., 1995). This result is also consistent with the work of Billings (2011) who found quite different results with different methods of identifying control areas to match given treatment areas, as well as different methods. As identified, the latter is well documented in the literature but the way in which capturing change through quasi experimental approaches using control and catchment areas can have quite different results depending on the choice of catchment and control areas is not well documented and something that future research must attend to if we are to have consistent and comparable results.

References

Alonso, W., 1964. Location and land use. Toward a general theory of land rent. Location and land use. Toward a general theory of land rent.

Athey, S., Imbens, G., 2002. Identification and inference in nonlinear difference-in-differences models. National Bureau of Economic Research Cambridge, Mass., USA.

Bertrand, M., Duflo, E., Mullainathan, S., 2002. How much should we trust differences-in-differences estimates? National Bureau of Economic Research.

Billings, S., 2011a. Estimating the value of a new transit option. Regional Science and Urban Economics 41, 525-536.

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

Card, D., Krueger, A.B., 1993. Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania. National Bureau of Economic Research.

Cervero, R., Duncan, M., 2002. Benefits of proximity to rail on housing markets: Experiences in Santa Clara County. J. Public Transp. 5.

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

Chernobai, E., Reibel, M., Carney, M., 2011. Nonlinear spatial and temporal effects of highway construction on house prices. The Journal of Real Estate Finance and Economics 42, 348-370.

Daniels, R., Mulley, C., 2013. Explaining walking distance to public transport: The dominance of public transport supply. Journal of Transport and Land Use 6, 5-20.

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.

Economides, N., 1996. The economics of networks. International journal of industrial organization 14, 673-699.

Gatzlaff, D.H., Smith, M.T., 1993. The impact of the Miami Metrorail on the value of residences near station locations. Land Econ., 54-66.

Golub, A., Guhathakurta, S., Sollapuram, B., 2012. Spatial and temporal capitalization effects of light rail in phoenix from conception, planning, and construction to operation. Journal of Planning Education and Research 32, 415-429.

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.

Katz, M.L., Shapiro, C., 1994. Systems competition and network effects. The journal of economic perspectives 8, 93-115.

Knaap, G.J., Ding, C., Hopkins, L.D., 2001. Do plans matter? The effects of light rail plans on land values in station areas. Journal of Planning Education and Research 21, 32-39.

Landis, J., Guhathakurta, S., Huang, W., Zhang, M., Fukuji, B., 1995. Rail transit investments, real estate values, and land use change: a comparative analysis of five California rail transit systems.

Loomis, J., Santiago, L., de Jesus, Y.L., 2012. Effects of construction and operation phases on residential property prices of the Caribbean's first modern rail transit system. Urban Public Economics Review, 56.

McDonald, J.F., Osuji, C.I., 1995. The effect of anticipated transportation improvement on residential land values. Reg. Sci. Urban Econ. 25, 261-278.

McMillen, D.P., McDonald, J., 2004. Reaction of house prices to a new rapid transit line: Chicago's midway line, 1983–1999. Real Estate Econ. 32, 463-486.

Mulley, C., Ma, L., Clifton, G., Yen, B., Burke, M., 2016. Residential property value impacts of proximity to transport infrastructure: An investigation of bus rapid transit and heavy rail networks in Brisbane, Australia. J. Transp. Geogr. 54, 41-52.

Mulley, C., Tsai, C.-H.P., 2016. When and how much does new transport infrastructure add to property values? Evidence from the bus rapid transit system in Sydney, Australia. Transp. Policy.

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.

Seneviratne, P.N., 1985. Acceptable Walking Distances in Central Areas. J. Transp. Engrg. Journal of Transportation Engineering 111.

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.

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