WORKING PAPER

ITLS-WP-21-07

The Value of Green Infrastructure: Evidence from the Gold Coast, Queensland, Australia

By
Barbara T.H. Yen[a,b], Corinne Mulley[c]
Heather Shearer[d]

[a] Department of Transportation and Logistics Management, National Yang Ming Chiao Tung University, Taiwan.
[b] Department of Transportation and Logistics Management, National Chiao Tung University, Taiwan.
[c] Institute of Transport and Logistics Studies, The University of Sydney, Sydney, Australia.
[d] Cities Research Institute, Griffith University, Gold Coast, Australia.

April 2021

ISSN 1832-570X

INSTITUTE of TRANSPORT and LOGISTICS STUDIES

The Australian Key Centre in
Transport and Logistics Management

The University of Sydney

Established under the Australian Research Council's Key Centre Program.

NUMBER: Working Paper ITLS-WP-21-07

TITLE: The Value of Green Infrastructure: Evidence from the Gold Coast, Queensland, Australia

ABSTRACT: Green infrastructure is important to underpin residential choice, provide sustainable transport and contribute to a liveable neighbourhood. This study investigates the value of green infrastructure to property owners where green infrastructure is defined as including built environment features (e.g., green spaces, beach), facilities (e.g., fitness equipment in parks) and infrastructure (e.g., heavy rail, light rail). Gold Coast, Queensland, Australia is the case study. To capture geographical differences across the city, a multi-level regression modelling approach is used to measure the implicit value of green infrastructure in the property price. The results suggest only those elements of green infrastructure that can provide a service (e.g., fitness equipment) are positively valued. Importantly from a sustainable transport perspective, the current public transport network and services make a negative contribution to property price suggesting these might not meet with residents' expectation. The conclusions of the paper discuss the implications of this for literature and policy in respect of green infrastructure.

KEY WORDS: ***Green infrastructure, value uplift, built environment, urban form, property value, sustainable transport***

AUTHORS: **Yen, Mulley, Shearer**

ACKNOWLEDGEMENTS: This study was partially sponsored by the Ministry of Science and Technology, ROC, under the contract number 109-2221-E-009 -047-MY3.

CONTACT: INSTITUTE OF TRANSPORT AND LOGISTICS STUDIES (H04)

The Australian Key Centre in Transport and Logistics Management
The University of Sydney NSW 2006 Australia
Telephone: +612 9114 1813
E-mail: business.itlsinfo@sydney.edu.au
Internet: http://sydney.edu.au/business/itls

DATE: April 2021

1. Introduction

The concept of sustainable transport has been incorporated in many city plans with the intention to reduce car dependency and significantly increase levels of active transport and public transport use. This is especially important for a car-dominated city, such as Gold Coast, Queensland, Australia. Gold Coast City Council aims to promote a sustainable transport environment to make the Gold Coast a better place to live, work and play (Gold Coast City, 2013). Transport accessibility is one of the key policy levers to achieve this goal. To encourage citizens to use public transport or active transport, a strong push and pull factor could be infrastructure availability, which can be evaluated by understanding the local built environment. Wang and Chen (2017) mention that a 'fair community development framework' could be shaped by a proper land use and transport planning strategy that would also remedy spatial inequality by understanding the spatial variation of built environment.

The built environment has been evaluated from many different aspects, such as human behaviour (Handy et al., 2002), travel behaviour (Ewing & Cervero, 2001; Saelens & Handy, 2008), accessibility (Pirie, 1979; Lamíquiz & López-Domínguez, 2015) and equity (Wang & Chen, 2017). Handy et al. (2002) explored how the built environment affects physical activity that in turn has impacts on different travel behaviour, such as walking. Saelens and Handy (2008) reviewed previous studies regarding walking as a physical activity and concluded that several built environments characteristics have positive impacts on walking, including transport and density; distance to non-residential destinations; and mixed land use. Further, households tend to select the neighbourhood that matches their travel behaviour, especially if they prefer to use active transport (Cao et al., 2009).

Residential location choice, which can be subject to residential self-selection, are based on households' travel ability, preferences and needs (Litman & Steele, 2017). Van Acker (2021) gave an example of how a particular household chooses a residential location with good public transport service because of their preference for using public transport, even though they may need to pay a higher property price. Some research has found that specific services (e.g., health care and shopping facilities) have positive impacts to property price (Ding et al., 2010). This suggests that the external built environment has an impact which has been internalised to the property price. The question now becomes: how much value has been placed on the value of built environment and infrastructure by individual householders?

This paper uses Gold Coast, Queensland, Australia as the case study to explore how property owners value green infrastructure, which is defined here to include built environment features (e.g., green spaces, beach), facilities (e.g., fitness equipment in parks) and infrastructure (e.g., heavy rail, light rail). In line with Lancaster's demand theory (Lancaster, 1966), the demand for a property is made up of a number of attributes each of which has an implicit price. This lays the groundwork for looking at hedonic type models where the different attributes that make up the price of a property show their implicit prices. For example, new transport infrastructure is expected to have an impact on property price due to the improvement of accessibility and this has been quantified through studies looking at value uplift for different modes such as heavy rail (Mulley et al., 2016; Sharma & Newman, 2018), light rail (Yen et al., 2018; Song et al., 2019; Yen et al., 2019) and bus rapid transit (Mulley & Tsai, 2016; Zhang et al., 2020). This paper proceeds by implementing this understanding with respect to green infrastructure, using similar methods to evaluate what implicit value householders have placed on the different amenity types, such as parks, fitness equipment, and playgrounds in their property price.

This paper is structured as follows. The next section provides a literature context for the study before turning to the introduction of the case study area, Gold Coast, Queensland, Australia. Then, the methodology used in this paper is outlined together with data descriptions before providing model results with interpretation. Finally, the paper concludes with some policy implications.

2. Literature context

This section briefly contextualises this study. First, in respect to why green infrastructure is important and why accessibility to it might be positively valued by property owners. Next, this section argues for the approach of disaggregating the property price into relevant attributes so as to identify their implicit price. Finally, the section argues for the use of multi-level regression modelling in the analysis.

Open space and amenities play an important role since they can offer great benefits to economic, social and environment (Cao et al., 2021). Caplan et al. (2121) measured the willingness to pay for different residential amenities and found significant differences in preferences that are in line with Cao et al. (2021). In previous studies, different amenities have been evaluated, such as forests, parks, golf courses, and wetlands (Ding et al., 2010; Netusil, 2013; Xiao et al., 2016; Farja, 2017). The interest in these evaluations initially came from urban planning highlighting a need to understand the two way interaction between accessibility and location of economic activity (Wachs & Kumagai, 1973). In turn, this has led to the importance of accessibility measurement in its contemporary role in the evaluation of urban and transport policy and the understanding of the links between land use planning and transport. Whilst evaluating the impacts for different amenities, households tend to capitalise their willingness to pay into property price (Cao et al., 2021).

In common with other investigations using property prices (such as land value uplift, emissions valuation), this paper assumes a property price is made up of a number of attributes, in line with Lancaster's demand theory (Lancaster, 1966) and, in turn underpins the use of hedonic analysis which puts an implicit price on the different elements that make up the property price. Whilst it is clear that the property characteristics, such as the number of bedrooms etc., will affect the price, it is also the case that local neighbourhood characteristics such as the numbers of older people in the population and built environment attributes such as access to park are also elements of a property price that analysis has shown to have an implicit value. These ideas have underpinned the literature on value uplift following the introduction of new transport infrastructure (for example, Mulley (2014), Sharma and Newman (2018), Song et al. (2019), Zhang et al. (2020)). The analysis in this paper develops this approach to examine how the property price is influenced by accessibility to green infrastructure.

In terms of the modelling of accessibility, there are number of different approaches that have been used to capture the effect of infrastructure on land value. The basic modelling approach simply disaggregates the property price into implicit prices for the property attributes using a hedonic regression model (Du & Mulley, 2007; Ding et al., 2010; Netusil, 2013; Xiao et al., 2016; Farja, 2017). However, this approach fails to take account of spatial relationships and the external characteristics (e.g., land use changes) for the selected study areas (Mulley & Tsai, 2016). To remedy this, other modelling approaches have been widely used for panel data of property prices include difference in differences modelling and multi-level regression modelling (Yen et al., 2019) with the multi-level regression model appearing to give better results, especially in the context of Gold Coast. In this paper, similar analytical tools are used to specifically investigate whether access to green infrastructure is valued by property owners using a multi-level regression modelling approach.

3. Case study: Gold Coast, Queensland, Australia

This study uses Gold Coast in Queensland, Australia, as the context to explore the research aims. Gold Coast is the sixth-largest city in Australia and is a typical coastal city that stretches for 57 kilometres of coastline, famous for its rich tourism attractions, especially for its beach views and water activities. Typically, Gold Coast hosts more than 10.5 million visitors per year; this increases pressure on the city's facilities and infrastructure and the ability to meet the needs of local residents (City of Cold Coast, 2013). Throughout the area, there are different built environment features, facilities and infrastructure as shown in Figure 1 which shows the green infrastructure – more specifically the beach facilities, play equipment, fitness equipment, dog exercise areas, other parks, major roads, heavy rail and light rail lines and stations. It is no surprise that most of the facilities are along the coastline. Recently, in a move to improve sustainable transport, the Gold Coast Light Rail Transit (GCLRT) opened in 2014 with an extension (stage 2) in 2017. GCLRT stage 2 extends GCLRT to a nearby heavy rail station (Helensvale Station) to connect to Brisbane, the capital city in Queensland.

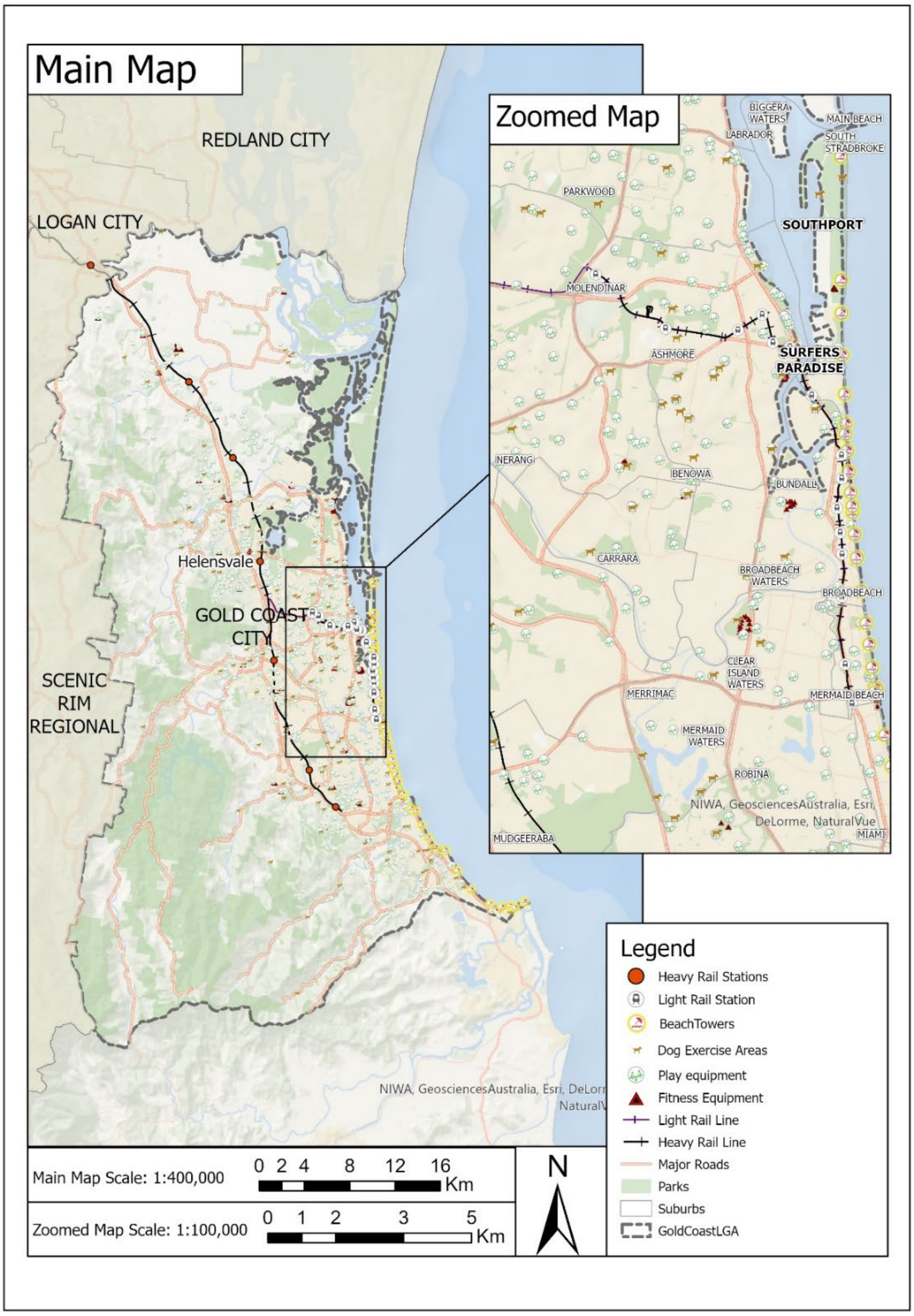

Figure 1 The map of Gold Coast with main attractions.

4. Methodology and data

This paper aims to investigate the implied contribution of green infrastructure to the property price. A multi-level regression modelling approach is used to group properties by geographical areas. The following sections review this modelling approach and present the description of the data used in the analysis.

4.1 Multi-level regression model

This study evaluates whether access to different facilities and infrastructure have impacts on the property price. Property prices are inherently spatial as a result of properties themselves being influenced by other properties in the neighbourhood and neighbourhood attributes. Multi-level modelling is used to control for spatial interdependence. A general multi-level regression is defined as:

$$\ln(p_{ik}) = \beta_0 + \beta_1 X_{ik} + u_k + \varepsilon_{ik} \tag{1}$$

where, p_{ik} represents the sale price of property i located in a neighbourhood k is predicted by a vector of observable attributes, X_{ik}. The error term includes two parts, a neighbourhood level error term u_k and an individual property level error term ε_{ik}. In the multi-level regression model, the variation of the property price is the sum of the variation of individual property level and the neighbourhood level.

Equation (2) builds on Equation (1) for the case study to include attributes in the model. Equation (2) is shown as follows:

$$\ln(p_{ik}) = \beta_0 + \sum_j \alpha_j P_{ijk} + \sum_j \beta_j N_{ijk} + \sum_j \delta_j A_{ijk} + \sum_t \theta_t year_{itk} + u_k + \varepsilon_{ik} \tag{2}$$

where, p_{ik} represents the transaction price of property i located in a neighbourhood k. Explanatory variables include a vector of property attributes (P_{ijk}) and neighbourhood attributes (N_{ijk}) as well as accessibility attributes (A_{ijk}). Time dummy variables ($year_{itk}$) are introduced to capture price changes and inflation, where t =1 if property is sold in 2016 (as this study uses data from 2015 and 2016). The parameters of interest are the accessibility attributes with the coefficients δ_j to identify the implicit price contribution of the green infrastructure to the property price.

4.2 Data descriptions

Table 1 summaries the details of variables used in the model. Variables have been categorised into four categories, and the following subsections introduce information on each category in turn for all variables significant in the model. Figure 2 show property price in the study area with different property types.

4.2.1 Dependent variable

This model uses the market clearing property price as the dependent variable provided by RP data for 2015 and 2016. This model relates to residential properties only since the interest is in how much value homeowners put on green infrastructure. The study area encompasses the whole Gold Coast in Queensland, Australia. For modelling, the property price is transformed to natural logarithms in the model to mitigate heteroscedasticity and reduce the scale of values (Rodríguez & Mojica, 2009; Yen et al., 2018). Table 2 shows the descriptive statistics results for the variables used in the model.

4.2.2 Property attributes

RP data provide several property attributes, such as property type (house, townhouse or apartment), area size, number of bedrooms. Whilst the area size of the property would be a useful metric, this cannot be used for Australian data as the area size captured by sales is the total land area, not the internal floor area and thus would give a misleading attribute for apartments. This study uses three property attributes in the model: property type, the number of bathrooms and the number of parking spaces. Property type is divided into house and apartment with house including both house and townhouse. From Figure 2, it is very clear that apartments are mostly located along the coastline.

4.2.3 Neighbourhood attributes

Neighbourhood data is sourced from the Australian Bureau of Statistic census data in 2016 at the Statistical Area 1 (SA1)[1] level as the property data refers to 2015 and 2016. The neighbourhood attributes include the percentage of elderly people (aged 65 plus), the percentage of the population with college and higher education degree, the percentage of household who have a mortgage of over AUD $25,000 annually, the percentage of English only speaking people, the percentage of married people, the percentage of migrant (first generation), and the percentage of population using all forms of public and active transport to work.

4.2.4 Time series variable

Since the data is collected for 2015 and 2016, a dummy variable of 2016 is set for the model to capture the price change and inflation over these two years.

4.2.5 Accessibility attributes

---

[1] An SA1 is the new geographical base unit for the 2011 Census and is the smallest level at which census data is reported having an average population of 400 persons.

Accessibility attributes were calculated using Geographic Information System (GIS). Accessibility attributes can be calculated by reference to network distance (Yen et al., 2018), a catchment dummy (Mulley et al., 2017) or travel time (Mulley, 2014). This study created four types of accessibility variables, including distance, house interaction with distance terms, catchment dummies, and catchment distance.

Distance variables were calculated as the road network distance from property to facilities, amenities and attractions, including schools, small parks (under 1 hectare), large parks, fitness equipment in park, beach, dog exercise areas, the Central Business Districts (CBD) of Southport, and Surfers Paradise, heavy rail stations, light rail stations, bus stations and highway exits.

A second accessibility variable type made use of interaction terms. Gold Coast is a linear city, and most apartments are located alone light rail corridors or along the coastline (Figure 2). In contrast, houses or townhouses tend to locate in the suburban areas that are usually further away from the light rail corridors. Therefore, it might be expected that different facilities would be worth more to houses vis a vis apartments and vice versa. In order to reflect these differences, two variables are used, a house interaction term with the network distance to the local shopping centre and distance to the nearest heavy rail station. So, for example, the house interaction term for shopping centre is the network distance to the closest shopping centre multiplied by 1 for house and 0 for apartment giving the network distance to the closest shopping centre as the house value and zero for the apartment.

The third type of accessibility variable relates to facilities with limited geographic impact. For example, transport services have a limited sphere of influence with a catchment area of, for example, one kilometre around the station being set for heavy rail. This assumes properties located beyond this distance might not be influenced by heavy rail. To be more inclusive, this study uses a one kilometre radius around heavy rail, light rail and bus stations as the catchment area. Being in the catchment of Southport CBD is defined as being within a one kilometre radius of Southport.

The final category of accessibility variables is catchment distance. This category is built on top of catchment dummies. For selected facilities and infrastructure, catchment dummies are created and their network distances interacted with each property to identify properties inside and outside the catchment area.

Table 1 Description of variables

Variables	Description
Property attributes	
Baths	number of bathrooms
Parking	number of parking spaces
House	=1 if property type is house or townhouse; =0 otherwise
Neigbourhood attributes	
65Plus	The percentage of elderly people (aged 65 plus)
Graduate	The percentage of the population with college and higher education degree
High Mortgage	The percentage of household who have a mortgage of over AUD $2.5k
English Speak	The percentage of English only speaking people
Married	The percentage of married people
Migrant	The percentage of migrant (first generation)
PT and Active Commuter	The percentage of population using all forms of public and active transport to work
Time series variable	
Year2016	=1 if property is sold in 2016; =0 if property is sold in 2015.
Accessibility attributes	
Distance	
School_km	Network distance from nearest school - all schools (Km)
Small park_km	Network distance to the centroids of small parks (under 1 hectare) (Km)
Large park_lm	Network distance to park junctions (large parks) (Km)
Fit_km	Network distance from fitness equipment in park (Km)
Beach_km	Network distance from beach (Km)
Dog_km	Network distance from dog exercise area in park (Km)
Southport_km	Network distance from property to Southport (CBD)
Surfers_km	Network distance from property to Surfers Paradise (major tourism site)
Heavy_km	Network distance from property to the nearest Heavy Rail station
Bus_km	Network distance from property to the nearest bus station
Hwy_km	Network distance from property to the nearest Highway exit
House interaction term	
House_Shop_km	Network distance from the closest shopping centre (Km) and if property type is house or townhouse
House_HR_km	Network distance from property to the nearest Heavy Rail station and if property type is house or townhouse
Catchment dummies	
Southport_catchment	=1 if property is located within 1km catchment areas of the Southport; =0 otherwise.

HR_catchment	=1 if property is located within 1km catchment areas of the nearest Heavy Rail station; =0 otherwise.
Bus_catchment	=1 if property is located within 1km catchment areas of the nearest bus station; =0 otherwise.
Catchment distance	
HR_Catch_km	Network distance from property to the nearest Heavy Rail station and if property is located within 1km catchment areas of the nearest Heavy Rail station
LR_Catch_km	Network distance from property to the nearest Light Rail station and if property is located within 1km catchment areas of the nearest Light Rail station
Bus_Catch_km	Network distance from property to the nearest bus station and if property is located within 1km catchment areas of the nearest bus station

The descriptive statistics of the variables for each year are presented in Table 2. This shows that the data are roughly equally distributed over two years although the property sale price is distinctly skewed. 1.4 % properties' sale price is over AUD $2 million and these fall more than 1.5 times of the interquartile range above the third quartile. Therefore, those properties are treated as outliers and excluded from the analysis.

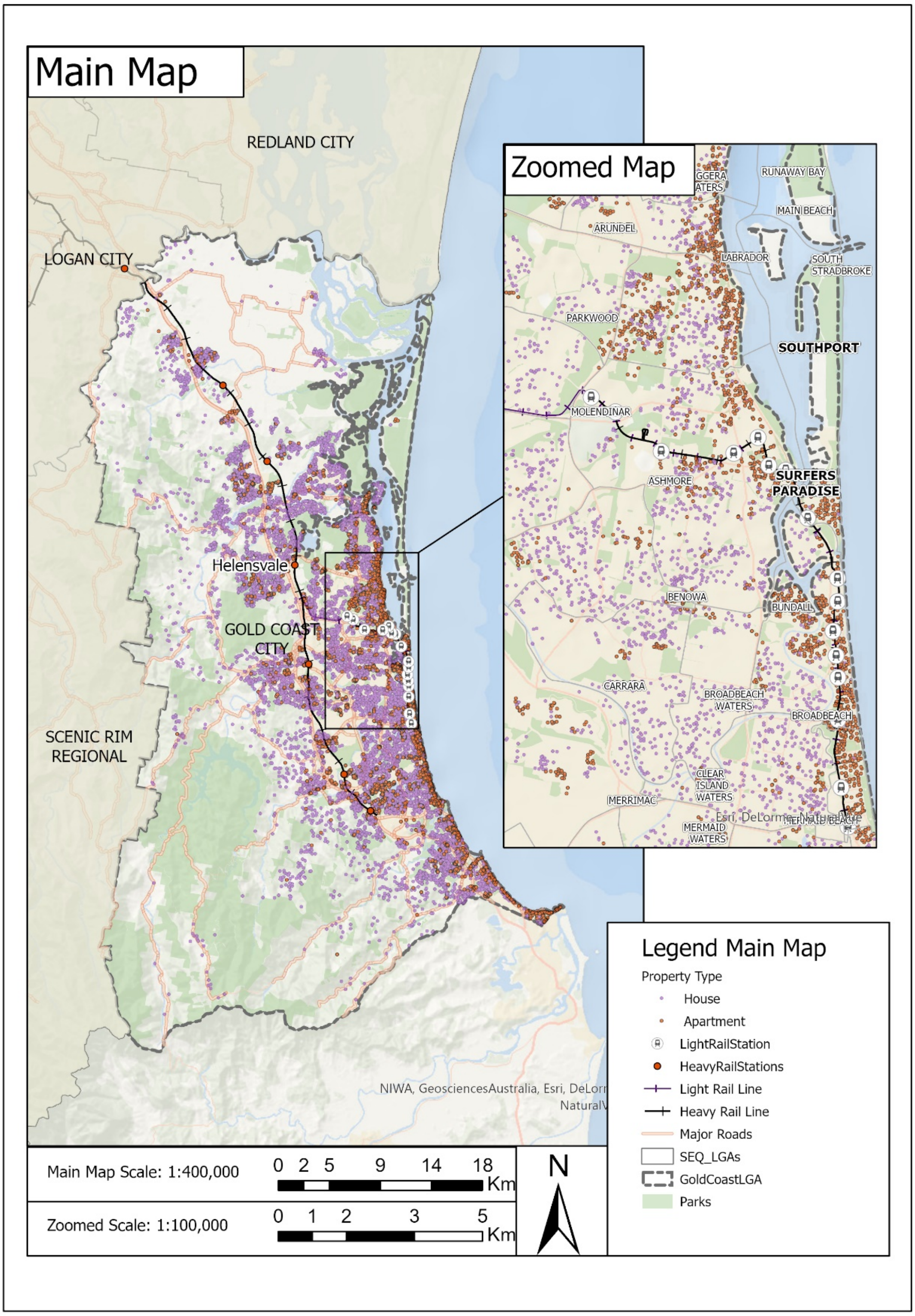

Figure 2 Property price data in the Gold Coast

Table 2 Descriptive statistics of the variables for each year

Variables	unit	All (n=18665)						House (n=9381)						Apartment (n=9284)					
		min	max	average	Standard deviation	Skewness	Kurtosis	min	max	average	Standard deviation	Skewness	Kurtosis	min	max	average	Standard deviation	Skewness	Kurtosis
EventPrice	10,000	11.500	199.000	55.500	27.880	1.746	3.998	12.500	199.000	56.780	28.600	1.714	3.710	11.500	199.000	54.230	27.060	1.775	4.307
Property attributes																			
Baths	number	0.000	8.000	1.501	1.032	0.052	0.004	0.000	8.000	1.529	1.024	0.041	0.105	0.000	7.000	1.472	1.040	0.066	-0.089
Parking	number	0.000	22.000	1.546	1.332	1.769	9.386	0.000	14.000	1.573	1.314	1.601	6.703	0.000	22.000	1.518	1.350	1.932	11.864
House	dummy	0.000	1.000	0.535	0.499	-0.139	-1.981	0.000	1.000	0.544	0.498	-0.175	-1.970	0.000	1.000	0.526	0.499	-0.102	-1.990
Neighbourhood attributes																			
65Plus	%	0.000	1.009	0.162	0.104	2.184	9.840	0.000	0.979	0.162	0.105	2.217	10.337	0.000	1.009	0.163	0.103	2.149	9.308
Graduate	%	0.000	0.411	0.149	0.052	0.118	0.199	0.000	0.411	0.148	0.052	0.168	0.274	0.000	0.411	0.149	0.052	0.068	0.124
High Mortgage	%	0.000	0.363	0.064	0.065	1.316	1.520	0.000	0.363	0.065	0.066	1.334	1.610	0.000	0.363	0.063	0.065	1.294	1.413
English Speak	%	0.000	1.154	0.776	0.141	-1.953	5.469	0.000	1.154	0.779	0.139	-2.078	6.389	0.000	1.154	0.772	0.143	-1.835	4.645
Married	%	0.000	1.000	0.364	0.098	0.250	3.156	0.000	1.000	0.365	0.098	0.255	3.238	0.000	1.000	0.364	0.097	0.244	3.071
Migrant	%	0.000	0.671	0.279	0.088	0.158	0.430	0.000	0.671	0.277	0.089	0.177	0.532	0.000	0.671	0.281	0.088	0.141	0.331
PT and Active Commuter	%	0.000	0.300	0.050	0.046	1.623	2.004	0.000	0.300	0.049	0.045	1.657	2.166	0.000	0.300	0.051	0.046	1.590	1.848
Time series variable																			
Year2016	dummy	0.000	1.000	0.503	0.500	-0.010	-2.000	-	-	-	-	-	-	-	-	-	-	-	-
Accessibility attributes																			
Distance																			
School_km	km	0.010	7.890	1.078	0.827	2.678	10.166	0.010	7.890	1.076	0.833	2.648	9.945	0.010	7.560	1.080	0.821	2.710	10.404
Small park_km	km	0.000	4.900	0.301	0.300	4.337	30.962	0.000	4.900	0.299	0.299	4.417	33.300	0.000	4.000	0.303	0.300	4.258	28.665
Large park_lm	km	0.000	2.120	0.159	0.161	3.615	20.677	0.000	2.120	0.158	0.162	3.670	20.989	0.000	2.110	0.160	0.160	3.558	20.369
Fit_km	km	0.010	19.630	1.402	1.276	3.976	31.200	0.010	16.800	1.404	1.231	3.275	20.588	0.020	19.630	1.399	1.320	4.540	39.061
Beach_km	km	0.040	32.690	5.861	5.965	1.345	1.626	0.040	32.200	5.958	6.016	1.316	1.491	0.050	32.690	5.763	5.912	1.375	1.771
Dog_km	km	0.040	13.910	0.957	0.825	4.266	33.577	0.040	10.680	0.959	0.820	3.706	23.243	0.040	13.910	0.954	0.830	4.813	43.556
Southport_km	km	0.032	33.952	9.535	6.424	0.728	0.088	0.058	33.930	9.636	6.395	0.709	0.051	0.032	33.952	9.434	6.452	0.748	0.127
Surfers_km	km	0.032	33.952	8.269	6.339	0.821	0.409	0.058	33.930	8.375	6.330	0.805	0.367	0.032	33.952	8.162	6.346	0.839	0.454
Heavy_km	km	0.020	21.780	5.277	2.799	1.086	2.609	0.020	18.510	5.242	2.771	1.033	2.350	0.090	21.780	5.313	2.827	1.135	2.841
Bus_km	km	0.000	19.650	0.425	0.998	8.506	100.153	0.000	16.330	0.420	0.939	7.595	77.057	0.000	19.650	0.431	1.054	9.083	112.636
Hwy_km	km	0.070	21.970	3.999	2.704	0.367	-0.545	0.070	18.180	3.964	2.679	0.313	-0.944	0.080	21.970	4.034	2.728	0.417	-0.177
House interaction term																			
House_Shop_km	km	0.000	21.990	3.148	4.132	1.448	1.643	0.000	20.480	3.255	4.195	1.387	1.403	0.000	21.990	3.040	4.064	1.513	1.914
House_HR_km	km	0.000	21.780	2.386	2.813	1.205	1.832	0.000	18.510	2.436	2.821	1.124	1.304	0.000	21.780	2.335	2.804	1.288	2.393
Catchment dummies																			
Southport_catchment	dummy	0.000	1.000	0.061	0.240	3.660	11.399	0.000	1.000	0.058	0.234	3.775	12.250	0.000	1.000	0.064	0.240	3.550	10.628
HR_catchment	dummy	0.000	1.000	0.022	0.146	6.575	41.236	0.000	1.000	0.022	0.146	6.576	41.257	0.000	1.000	0.022	0.146	6.575	41.239
Bus_catchment	dummy	0.000	1.000	0.787	0.410	-1.400	-0.041	0.000	1.000	0.787	0.410	-1.399	-0.042	0.000	1.000	0.787	0.410	-1.400	-0.039
Catchment distance																			
HR_Catch_km	km	0.000	0.990	0.015	0.107	7.352	54.087	0.000	0.990	0.015	0.105	7.498	56.478	0.000	0.990	0.016	0.110	7.214	51.881
LR_Catch_km	km	0.000	0.800	0.062	0.153	2.776	7.369	0.000	0.800	0.060	0.152	2.793	7.432	0.000	0.800	0.063	0.154	2.760	7.308
Bus_Catch_km	km	0.000	0.400	0.144	0.111	0.308	-0.843	0.000	0.400	0.145	0.111	0.289	-0.865	0.000	0.400	0.144	0.111	0.327	-0.821

5. Model results

This study constructs a multi-level regression model. Table 3 shows the regression model results where the independent variables are all statistically significant at the 0.01 level. The multi-level regression model, as shown by rho, captures 8.3 percent of variation within the neighbourhood level. The results concentrate on looking at the accessibility to green infrastructure variables in line with the research aim of this paper with only brief reference to other variables.

Property attributes, neighbourhood attributes and time series variable

All property attributes have positive coefficients as expected. The property type of house has a 31.2% higher price than apartment type on average. It is typical for Australian cities for houses to have a higher price than apartments.

Most neighbourhood attributes also show the expected sign with property prices being higher in neighbourhoods with a larger elderly population; residents with college and higher qualifications; higher mortgage payments; and a bigger married population. In contrast, property prices are lower if there is a larger English only speaking population and a bigger migrant population. It is also the case, unexpectedly, that neighbourhoods with more public transport or active transport users have lower property prices. This might be due to property location since most apartments are located along the light rail corridor (within 400 meters of light rail, 96.4% of the properties are apartments) giving the opportunity for those households to use public transport more or undertake active transport. Yen et al. (2018) show that the house price is double that of an apartment price in the 400m catchment are for the light rail in Gold Coast. This supports the negative connection between public transport and active transport usage and property price.

The time dummy variable is significant confirming successfully capturing the 3.6% increase in price for properties sold in 2016 compared with 2015.

Accessibility attributes

Accessibility attributes are the particular variables of interest in this paper for evaluating green infrastructure features. Each of the four types of accessibility attributes (discussed above) are discussed in turn. Some green infrastructure features are part of more than one accessibility attributes, for example, heavy rail. The overall effects for these features are discussed at the end of this section.

Distance variables use the network distance from each property to each specific feature. Within the study area, access to the nearest school does not bring a positive premium to property price. This might due to school type and/or school quality as these are not taken into account in this analysis. Surprisingly, green infrastructure in the form of a park also does not bring positive impact: for each one kilometre closer to a small park, the property price decreases by 6.4% and by 8.2% for a large park. In contrast, green infrastructure features with a specific function bring a positive premium to the property price. This includes access to fitness equipment, beach, and dog excise areas, bringing average property premiums of 2.7%, 2.5% and 1.4% respectively for every kilometre closer to the feature. On average too, property prices are higher when the property is located closer to the CBD (Southport) but not the tourism centre of Surfers Paradise. Transport infrastructure also has mixed results with a positive premium arising from access to heavy rail and bus infrastructure but negative premium is observed for access to highway infrastructure.

The interaction terms for house is the second type of accessibility variable. If the property type is house, property prices are on average higher when the property is located closer to local shopping centre or further away from a heavy rail station. For the catchment variables, the model results show that all catchment variables bring negative impact to property prices. So, if a property is located within the catchment area of a heavy rail station, bus station, or CBD (Southport) the property prices are lower by 21.1%, 15.9% and 11.9%, respectively. Last but not least, the public transport related catchment distance variables show a negative impact on property prices. For the properties within the catchment areas, each one kilometre closer to the heavy rail station decreases the property price by 36.2% and this would be 6.2% for light rail and 42.2% for bus.

Some green infrastructure features included in the model have been measured in more than one way for accessibility. For example, the overall impact for a property located within heavy rail catchment area can therefore be discussed in a number of ways. First, its property price is 21.1% lower than others located outside a heavy rail catchment area. Second, within the catchment area, each one kilometre closer to the heavy rail station decreases the property price by 34.3% (= -1.9% from distance variable and 36.2% from catchment distance variable). Third, if this property is a house, each one kilometre closer to the heavy rail station further decreases the property price by 3.0% giving a total 37.3%. To put this in perspective, as the average property price in the study area is AUD $555,000, this relates to a decrease of AUD $20,701 per 100 metres closer to a heavy rail station. Access to bus also can be evaluated similarly. For all properties, access to bus shows to bring price premium of

2.9% for every one kilometre closer to the closest bus stop. If other forms of accessibility are considered, access to bus brings an overall negative impact to the property price, especially for those located within the bus catchment areas. Access to light rail, on the other hand, is only significant if measured as a catchment distance when a significant negative impact is observed.

Table 2 Estimation results of multi-level regression model

Variable	Coefficient	P value	Variable	Coefficient	P value
Accessibility attributes			Intercept	**12.742**	**0.000**
Distance_km			**Property attributes**		
School_km	0.020	0.004	Baths	0.074	0.000
Small park_km	0.064	0.000	Parking	0.010	0.000
Large park_lm	0.082	0.001	House	0.312	0.000
Fit_km	-0.027	0.000	**Neigbourhood attributes**		
Beach_km	-0.025	0.000	65Plus	0.191	0.001
Dog_km	-0.014	0.034	Graduate	1.870	0.000
Southport_km	-0.029	0.000	High Mortgage	0.904	0.000
Surfers_km	0.053	0.000	English Speak	-0.389	0.000
Heavy_km	-0.019	0.000	Married	0.403	0.000
Bus_km	-0.029	0.000	Migrant	-0.453	0.000
Hwy_km	0.036	0.000	PT and Active Commuter	-0.652	0.006
House interaction term			**Time series variable**		
House_Shop_km	-0.014	0.000	Year2016	0.036	0.000
House_HR_km	0.030	0.000	**Model statistics**		
Catchment variable			Number of obs	18665	
Southport_catchment	-0.119	0.000	Random-effects Parameters:		
HR_catchment	-0.211	0.009	sd(_cons)	0.024	
Bus_catchment	-0.159	0.000	sd(Residual)	0.080	
Catchment km			rho	0.083	
HR_Catch_km	0.362	0.000	Log-likelihood	-3785.452	
LR_Catch_km	0.062	0.043	* Rho =sd(_cons)^2/(sd(_cons)^2+sd(Residual)^2)		
Bus_Catch_km	0.422	0.000			

6. Discussions and Conclusions

Green infrastructure is important in many aspects, including underpinning residential choice, sustainable transport provision and contributing to a liveable neighbourhood. This paper contributes to the literature by measuring the value of green infrastructure in terms of the implicit valuation of the infrastructure as part of the property price. A multi-level regression model is built to capture geographical differences across the study area of Gold Coast, Queensland, Australia.

The results show surprisingly that green infrastructure is not overwhelmingly positively valued. It is not clear why this is but whilst, for example, proximity to a park may appear desirable, this may come with side effects, such as a higher criminal rate (Taylor et al., 2019), the potential for antisocial behaviour (Andrews et al., 2017), and negative environmental impacts (e.g., flooding or pest). In contrast, green infrastructure which can provide services, such as fitness equipment and dog exercise areas, have a positive valuation as part of the property price. In other words, these results suggest residents are not just looking for green space, but for green infrastructure to play some part in their life if it is to provide a positive premium to their property price. Whilst not a study in valuation, Wu et al., 2020 found the same result with satisfaction (instead of value) as the dependent variable and it might be expected that valuation and satisfaction are positively related. Perhaps the most noticeable impact on property price comes from proximity to the beach as the model shows, as expected, property prices increase the closer one is to the beach. As a city famous for its beach views and activities, it is straightforward to see how Gold Coast benefits from positive impacts to property price from being close to the beach. However, it is not universal since, being located in the famous 'tourist playground' of Australia, Surfers Paradise, which is next to the beach is found to have a negative impact on property price: this is likely due to potential negative externalities of the neighbourhood.

There are three major public transport modes in Gold Coast: heavy rail, light rail and bus. For the whole Gold Coast, on average, every one kilometre closer to a heavy rail and bus station brings 1.9% and 2.9% positive contribution to property price showing that these modes are appreciated. The Gold Coast light rail is a newly introduced public transport mode and does not bring a significant impact to property at the city level suggesting there may be a lagged effect to recognise the benefits of light rail. However, within specific catchment areas (i.e., one kilometre in this study), significant and larger negative impacts to property prices are shown from all three public transport infrastructure modes. Whilst the Gold Coast has a clear policy to promote sustainable transport, this suggests that current public transport layout or service level do not meet the requirement of households well enough for them positively price their presence into the property price. Of course, other contributory factors to a negative contribution to property price might be due to unwanted side effects (e.g., population, crime, noise) which seem to be associated closer to the public transport infrastructure (Zhang et al., 2020).

By understanding how residents value green infrastructure, some policy implications can be proposed. It is clear that residents are heterogeneous in their valuation but that a positive valuation comes from green infrastructure which provides a service. This needs for the service element can be embedded in a localised regional plan to better fit the needs of neighbourhood. It is worth noting that proximity to public transport in Gold Cost (heavy rail, bus) is valued positively but when combined with the accessibility variables gives an overall, rather large, negative impact to the property valuation. This suggests that public transport *per se* is valued but in Gold Coast is not delivering the services that people living in proximity to it are demanding. This suggests that policy makers should review public transport service provision, in discussion with the public, to make public transport a more competitive transport mode vis a vis private modes, especially where public transport has good availability.

Further research needs to undertake more of a longitudinal analysis to investigate the timing effects of introducing green infrastructure and residents' attitude towards different types of green infrastructure. Future research could consider further segmentation of green infrastructure such as park types into a more finely grated type instead of just large or small. Classifying with respect to location, and function may well provide greater insight. Other relevant variables, such as public transport service frequencies, connections, provision of park-n-ride, are worthy to use to capture the characteristics of public transport services in better assessing the value householders place on the contribution of public transport accessibility to the property price.

Acknowledgements

This study was partially sponsored by the Ministry of Science and Technology, ROC, under the contract number 109-2221-E-009 -047-MY3.

References

Andrews, B., Ferrini, S., & Bateman, I. (2017). Good parks–bad parks: the influence of perceptions of location on WTP and preference motives for urban parks. *Journal of Environmental Economics Policy, 6*(2), 204-224.

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2009). Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. *Transport reviews, 29*(3), 359-395.

Cao, Y., Swallow, B., & Qiu, F. (2021). Identifying the effects of a land-use policy on willingness to pay for open space using an endogenous switching regression model. *Land use policy, 102*, 105183.

Caplan, A. J., Akhundjanov, S. B., & Toll, K. (2121). Measuring Heterogeneous Preferences for Residential Amenities. *Regional Science and Urban Economics*, 103646.

City of Cold Coast. (2013). *Gold Coast City transport strategy 2031*. Retrieved from

Ding, W., Zheng, S., & Guo, X. (2010). Value of access to jobs and amenities: Evidence from new residential properties in Beijing. *Tsinghua Science Technology, 15*(5), 595-603.

Du, H., & Mulley, C. (2007). The short-term land value impacts of urban rail transit: Quantitative evidence from Sunderland, UK. *Land use policy, 24*(1), 223-233.

Ewing, R., & Cervero, R. (2001). Travel and the built environment: a synthesis. *Transportation research record, 1780*(1), 87-114.

Farja, Y. (2017). Price and distributional effects of privately provided open space in urban areas. *Landscape research, 42*(5), 543-557.

Gold Coast City. (2013). *Gold Coast City Transport Strategy 2031*. Retrieved from https://www.goldcoast.qld.gov.au/documents/bf/GC-transport-strategy-2031.pdf

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. (2002). How the built environment affects physical activity: views from urban planning. *American journal of preventive medicine, 23*(2), 64-73.

Lamíquiz, P. J., & López-Domínguez, J. (2015). Effects of built environment on walking at the neighbourhood scale. A new role for street networks by modelling their configurational accessibility? *Transportation Research Part A: Policy Practice, 74*, 148-163.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy, 74*(2), 132-157.

Litman, T., & Steele, R. (2017). *Land use impacts on transport*: Victoria Transport Policy Institute Canada.

Mulley, C. (2014). Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. *Urban Studies, 51*(8), 1707-1724.

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. *Journal of transport geography, 54*, 41-52.

Mulley, C., Sampaio, B., & Ma, L. (2017). South eastern busway network in Brisbane, Australia: value of the network effect. *Transportation research record, 2647*(1), 41-49.

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. *Transport Policy, 51*, 15-23.

Netusil, N. R. (2013). Urban environmental amenities and property values: does ownership matter? *Land use policy, 31*, 371-377.

Pirie, G. H. (1979). Measuring accessibility: a review and proposal. *Environment Planning A, 11*(3), 299-312.

Rodríguez, D. A., & Mojica, C. H. (2009). Capitalization of BRT network expansions effects into prices of non-expansion areas. *Transportation Research Part A: Policy Practice, 43*(5), 560-571.

Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: a review. *Med Sci Sports Exerc, 40*(7 Suppl), S550-566. doi:10.1249/MSS.0b013e31817c67a4

Sharma, R., & Newman, P. (2018). Does urban rail increase land value in emerging cities? Value uplift from Bangalore Metro. *Transportation Research Part A: Policy Practice, 117*, 70-86.

Song, Z., Cao, M., Han, T., & Hickman, R. (2019). Public transport accessibility and housing value uplift: Evidence from the Docklands light railway in London. *Case studies on transport policy, 7*(3), 607-616.

Taylor, R. B., Haberman, C. P., & Groff, E. R. (2019). Urban park crime: Neighborhood context and park features. *Journal of criminal justice, 64*, 101622.

Van Acker, V. (2021). Urban Form and travel behavior: the interplay with residential self-delection and residential dissonance. In J. D. N. Corinne Mulley (Ed.), *Urban Form and Accessibility* (pp. 83-105). United State: Elsevier.

Wachs, M., & Kumagai, T. G. (1973). Physical accessibility as a social indicator. *Socio-Economic Planning Sciences, 7*(5), 437-456.

Wang, C.-H., & Chen, N. (2017). A geographically weighted regression approach to investigating the spatially varied built-environment effects on community opportunity. *Journal of transport geography, 62*, 136-147.

Xiao, Y., Li, Z., & Webster, C. (2016). Estimating the mediating effect of privatelysupplied green space on the relationship between urban public green space and property value: Evidence from Shanghai, China. *Land use policy, 54*, 439-447.

Yen, B. T., Mulley, C., & Shearer, H. (2019). Different stories from different approaches in evaluating property value uplift: evidence from the gold coast light rail system in Australia. *Transportation research record, 2673*(3), 11-23.

Yen, B. T., Mulley, C., Shearer, H., & Burke, M. (2018). Announcement, construction or delivery: When does value uplift occur for residential properties? Evidence from the Gold Coast Light Rail system in Australia. *Land use policy, 73*, 412-422.

Zhang, M., Yen, B. T., Mulley, C., & Sipe, N. (2020). An investigation of the open-system Bus Rapid Transit (BRT) network and property values: The case of Brisbane, Australia. *Transportation Research Part A: Policy Practice, 134*, 16-34.