Pacific Rim Property Research Journal, 2015
Vol. 21, No. 3, 199–214, http://dx.doi.org/10.1080/14445921.2016.1140715

The impact of transit-oriented development (TOD) on residential property prices: the case of Box Hill, Melbourne

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(*Received 8 November 2015; accepted 8 January 2016*)

Transit-oriented design (TOD) – an increase in density around transit stations – has arisen in many of Australia's capital cities as a way to encourage mass transit ridership as well as to efficiently utilize the increase in foot and vehicle traffic that transit stations create. However, the implementation of TODs in Melbourne has faced strong opposition due to residents' perception that the disamenities of a TOD will outweigh the benefits resulting in negative impacts on property prices. This research analyzes the relationship between proximity to a TOD and residential home prices. Results indicate that proximity to a TOD is positively related to property prices, even after controlling for neighborhood factors such as street connectivity and overall land use mix. By testing a variety of transformations of distance, we find that the benefits of TOD proximity extend approximately 1250 m from the Box Hill station. From a methodological standpoint, we find that more flexible treatments of distance variables in spatial autoregressive and spline models produce better model fit and lead to results more in line with urban economic theory.

Keywords: transit-oriented development; spatial autocorrelation; spline model; mass transit

Introduction

The concept of Transit-Oriented Development (TOD) arose in the early 1990s as a method to increase pedestrian travel and transit use, reducing automobile dependence, and improve the livability of the modern suburb (Calthorpe, 1993). At its core, TOD involves the planning, zoning, and construction of mixed-use communities and core commercial areas within an average 600-m walking distance of a transit station. Strategically, planners and developers focused on the three 'D's: Density, Diversity and Design. The key idea is that, by intensifying commercial development around stations, mixing land uses, and constructing pedestrian-friendly road networks and urban design, the built environment itself will allow and encourage more efficient travel behavior (Cervero & Kockelman, 1997; Sung & Oh, 2011).

The metropolitan Melbourne region has embraced TOD, as evidenced by the centrality of the TOD framework in the recent master plans. These include concepts such as 'Central Activities Districts', '20 Minute Cities' and 'Activity Centres' (DTPLI, 2002, 2008, 2014). While well intentioned, these policies aimed at increasing the density of developments within walking distance from major transit stations have received strong community opposition in some suburbs as many residents are under the impression that

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TODs will decrease the value of their properties. This study addresses that issue by estimating the impact of one suburban TOD – Box Hill – on the prices of nearby houses and townhomes. Box Hill is one of the more prominent suburbs in Melbourne that has incorporated the 3Ds concepts of TOD. To thoroughly investigate this problem in the context of TODs, the data is analyzed using three separate model specifications including distance, connectivity, and spatial error models (SEM). Furthermore, within each model we analyze four distinct treatments of distance – straight linear, log of distance, ring-based, and spline. Results show that home price decreases with distance from TOD across all model specifications, although the SEM outperforms others especially in the spline treatment of distance.

In the next section, we discuss TOD literature with specific focuses on (dis)amenity issues and distance models. Data sources and methods are identified in the third section, results discussed in the fourth, and our paper concludes with recommendations for further research.

Literature review

TODs and residential property prices

While many studies address the impact of transit stations on residential property values generally, few address the impact of TODs specifically. Differentiating between the two is of utmost importance to this research as well as to urban design and policy. Transit-Oriented Developments differ substantially from Transit Adjacent Development (TAD) in that they are designed to capitalize on density, pedestrians and a variety of land uses. TAD, conversely, is 'physically near transit [but] fails to capitalise upon this proximity … [It] lacks any functional connectivity to transit – whether in terms of land-use composition, means of station access or site design' (Cervero, Ferrell, & Murphy, 2002). Given the increasing number of developments using rail stations as an anchor, station precincts can transition from a TAD into a TOD giving rise to a development spectrum where TADs are 'failed' TODs or simply underdeveloped to qualify as a TOD (Cervero et al., 2004; Hale, 2014; Renne, 2009). However, because TADs are fundamentally similar to TODs, that literature is included in our discussion.

Theoretically, TODs are modern multi-centered urban centers which should exhibit the same bid-rent curve effect as the mono-centric CBD where an increase in relative accessibility translates into higher property prices (Hess & Almeida, 2007; Nelson, 1992). The accessibility of a property is generally measured by its proximity to the TOD. Existing studies show that the effect of proximity to transit stations on property values has mixed impacts with some studies showing a price premium (Cervero & Duncan, 2002; Damm, Lerman, Lerner-Lam, & Young, 1980; Grass, 1992; Kay, Noland, & DiPetrillo, 2014) and others a price discount (Dornbusch, 1975; Landis, 1995) or insignificant impact (Gatzlaff & Smith, 1993; Lee, 1973).

Cervero and Duncan (2002), Goetz, Ko, Hagar, Ton, and Matson (2010) and Landis (1995) show that price premiums are not equally distributed as commuter rail and light rail systems have a 'disamenity zone' where the disamenity of locating very close to the rail outweighs the accessibility benefits. Discounts in the disamenity zone are generally attributed to environmental issues such as noise, vibration, and increased crime. Conversely, when proximity from the station increases past a certain threshold, the accessibility benefits outweigh any disamenity effect. A meta analysis conducted by Debrezion, Pels, and Rietveld (2007) shows that the distance effect of proximity to transit stations results in a 2.4% average increase in price for every 250 m closer a property is to a station.

Mathur and Ferrell (2013) built 3 hedonic pricing models based on different time periods to address the impact of suburban TODs on nearby residential property value. Their models incorporate pre-, during, and post-TOD construction variables, finding no significant impact on value prior to, a 7.3% increase during, and a 18.5% increase after the completion of construction. Furthermore, they found that price effects were statistically insignificant after the 1/8 mile distance suggesting that the price differential dissipates quickly after a certain proximity from the TOD.

Measuring TOD impact

While there are many value-determining factors of a property, the common value-determining factors used by researchers can be categorized as: physical, accessibility, and environmental attributes (Brigham, 1965; Grether & Mieszkowski, 1974; Rosen, 1974). Desirable physical attributes of a property generally include larger lot size, building size, number of bathrooms and rooms, parking capacity, pools and new housing stock, whereas, physical attributes such as age and deterioration typically have an adverse effect on property value (Grass, 1992; Haider & Miller, 2000; Hui, Chau, Pun, & Law, 2007). These variables make up the traditional hedonic pricing model pioneered by Rosen in 1974.

se Can and Megbolugbe (1997) argue that the hedonic pricing model is limited in its ability to capture the geographic nature of the housing price phenomenon, suggesting the addition of a spatial lag variable to transform the hedonic pricing model into a spatial autoregressive hedonic pricing model. The results of their study show an 18% lower R-square in the simple hedonic model relative to that of the spatial hedonic model. Comparable results are found in Haider and Miller (2000), Hui et al. (2007) and Kay et al. (2014). In sum, the literature on hedonic price modeling suggesting that all primary value determining factors – physical, accessibility (location), and environmental (neighborhood) – must be accounted for, while difficult-to-measure spatial impact that remain can be controlled for with advanced spatial modeling techniques.

Study area and data

We selected Box Hill as the study area due to its long standing as a Transit-Oriented Development within Melbourne. Box Hill is an existing metropolitan activity center as identified in Plan Melbourne 2050 and it plays a major service delivery role to the residents in the Melbourne Inner East region (DTPLI, 2014). The station is currently serviced with multi-modal public transportation (train, tram, and bus). Box Hill underwent a major redevelopment in the 1980s which transformed its aging ground-level railway station into an underground station with an above-station shopping center; placing it as Melbourne's only underground station outside the city-loop stations. One of Melbourne's largest Metropolitan Activity Centre, the Box Hill area has a population of approximately 4,400 people, employment of 15,600 jobs, and a Gross Regional Product of $1.622 billion (DTPLI, 2014; EconomicProfile.com.au., 2015).

While an underground train station is the most expensive type of transit development, the benefit of choosing Box Hill as opposed to the other TODs in Melbourne is that the presence of a 'disamenity zone' due to the noise from the railway station is unlikely to distort the pricing model for the area studied. Additionally, most residential properties are buffered from the direct rail noise impact by the commercial area surrounding the railway station. Nevertheless, disamenities attributable to the commercial area such as noise, light, trash, traffic, and higher crime rates may still be present.

Our specific study area encompasses the approximate Box Hill station catchment area; areas in which Box Hill is the nearest rail station. To form realistic boundaries that likely mimic distinguishing features in the property market, our study area is bounded by major streets on the west (Elgar Road) and east (Dorking Road and Barkly Street) and by Bushy Creek Park to the north and approximately by Kingswood College to the south (See Figure 1). The entire study area is approximately 1.4 km east-west and 3.3 km north-south, or about 4.5 sq km in size.

The primary data source used to carry out this research was retrieved from the Australian Urban Research Infrastructure Network's (AURIN) online portal, an open-source e-research tool which interrogates, models and visualizes data from its various network collaboration across Australia through contracted subprojects and Data Access Agreements (AURIN, 2015). AURIN provided access to data on property sold, train stations, street networks, mesh blocks, and the walkability index tool from sources as shown in Table 1.

The property transaction data was gathered for a period of 10 years from 1 May 2006 to 31 May 2015. Only sales of single family detached homes and attached townhomes are included in the data-set. Standard physical characteristics information on the lot size, number of bedrooms, number of bathrooms and presence of a garage are available from the data source. Three important home characteristics, however, are missing; home size, home condition and year built or renovated. Here, we allow bedroom and bathroom counts to act as a rough proxy for home size. Most original homes in this

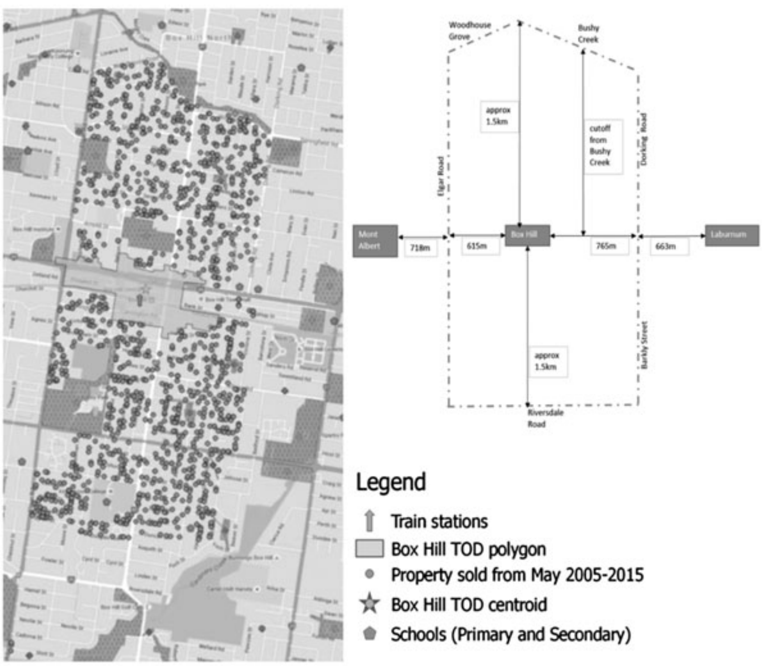

Figure 1. Box Hill Study Area.

Table 1. Data sources.

Data	Data source
Property transactions	Australian property monitors' victoria database
PSMA street network	PSMA Australia
Mesh Block 2011 census	Australian Bureau of Statistics
Walkability index	AURIN

area were built around the same period; therefore, we need only worry about new infill construction or major renovations. We utilize the variables indicating presence of a Study and a Walk-in Wardrobe as proxy variables for newer construction or renovations as new homes are more likely to have these amenities. While imperfect, these two proxies help address an unavoidable gap in the data source. Finally, information on structural condition is also lacking. As condition and home age/renovation are related, the Study and Walk-in Wardrobe variables may help identify homes in better-than-average condition as well, though certainly not all conditional difference will be captured by these proxies and a good portion of conditional differences will be represented in the error terms of our models.

The 'complete with gross density (points) walkability analysis' tool from AURIN utilized the data on the street network and Meshblock 2011 to generate a walkability index for each property sold (AURIN, 2015). The Centre for Built Environment and Health developed the walkability measure to generate z-scores for the street connectivity, land use mix for education, commercial and parkland uses, and average population density for a walking catchment of 1.5 km from each property sold. The commercial, parkland and education land uses were selected because these are desirable land uses that most people would like to locate close to (Learnihan et al., 2011). The walkability index is the sum of all three z-scores which represents how walkable each residence is for transportation or recreational purposes (AURIN, 2015).

As with all real estate data, there are likely data errors and outliers in the raw data collected from the source. We began the data cleansing process by excluding duplicated sale transactions. Next, we removed those observations with missing variables, either sale price, sale date or one of the independent variables mentioned above. Finally, we screened for potential data errors and or extraordinarily good or bad homes by removing properties with extremely high and low price per square meter). After the data cleansing, 1268 properties remained for constructing the pricing models. Table 2 provides a brief description of the independent variables included in the final models with some descriptive statistics.

Methods

Two standard methods are used when measuring the impact of an amenity (dis-amenity) on home prices. In instances where the amenity is a recent phenomenon with an unambigous origin date, a before-after analysis can be undertaken. In other situations, like the case of Box Hill, the amenity (the TOD station) has been in place for some time and was built out over a long time period. This situation necessitates analysis via proximity, or rather, a measurement of marginal price influences due to proximity to the amenity while carefullly controlling for other factors that may impact price.

Table 2. Summary statistics.

Variable	Type	Description	Mean	Min	Max	St Dev
Price	Dep – Continuous	Transaction price	798,793	263,000	2,300,000	298,994
QTR	Temporal Fixed Effect	Quarter of sale				
Lot size	Ind – Continuous	Lot size (m2)	583	90	1800	270
Beds	Ind – Continuous	# of bedrooms	3.10	1.00	6.00	.82
Baths	Ind – Continuous	# of bathrooms	1.55	1.00	4.00	.61
Dist to TOD	Ind – Continuous	Distance to TOD (km)	1116	188	1905	403
Garage	Ind – Binary	Presence of garage	.14	0	1	
Walk-in wardrobe	Ind – Binary	Presence of walk-in wardrobe	.11	0	1	
Study	Ind – Binary	Presence of study	.24	0	1	
Townhouse	Ind – Binary	Is a townhome	.16	0	1	
Ring 1	Ind – Binary	Location < 600 m from TOD	.22	0	1	
Ring 2	Ind – Binary	Location >= 750 m & < 1,250 m from TOD	.37	0	1	
Ring 3	Ind – Binary	Location >= 1,250 m from TOD	.41	0	1	
Street connectivity	Ind – Standardized (*Z*)	Measure of local street connectivity (1500 m radius)	.35	−1.36	2.04	.72
Land use mix	Ind – Standardized (*Z*)	Measure of local land use mix (1500 m radius)	.37	−.68	1.01	.04

We measure the influence of the Box Hill TOD on residential home prices through a hedonic pricing model. Originated by Rosen (1974), the hedonic pricing model uncovers the marginal implicity prices of individual home characteristics – characteristics which can be structural, neighborhood or locational in nature. In this case, we are interested in the price impacts of proximity to (or distance from) the Box Hill TOD. Analyzing distance impacts can be done a number of ways, depending on whether or not the impacts due to distance are believed to be strictly linear, non-linear or some other combination. In this paper we analyze the impact of distance four different ways (transformations): (1) linear; (2) log; (3) concentric rings; and (4) linear spline.

As mentioned above, it is important to properly control for other factors that are influencing home prices. These include physical, neighborood, and locational characteristics. Since our variable of interest – distance from TOD – is a locational variable, we must be sure to adequately control for other spatial influences in order to isolate the impact of distance on home prices. To do so, we have specified three progressively more complex models, where each subsequent model adds to our method of controlling for spatial influences in the models. In the initial model, we utilize a variety of structural (physical) control variables while accounting for location only through the distance to TOD variable. In this model, time-invariant temporal effects are controlled for with quarter fixed effects representing the quarter in which the transaction occurred. The resulting model (1) takes the following form:

$$\mathrm{Log}(P) = \alpha + \beta_1 T + \beta_2 P + \beta_3 D + \varepsilon \quad (1)$$

where P is the sale price, T is a vector of time fixed effects (quarterly) dummies, is a vector of physical attributes, D is the variable(s) representing distance to the TOD station, and ε is the error term. Model two (2) adds neighborhood or environmental variables (N); street connectivity and land use mix as calculated by AURIN's walkability analysis tool. Each of these variables is standardized to a Z-score for more straightforward comparison.

$$\mathrm{Log}(P) = \alpha + \beta_1 T + \beta_2 P + \beta_3 D + \beta_4 N + \varepsilon \quad (2)$$

Controlling for all spatial influences[1] on a given property is incredibly difficult and as a result, omitted variable bias can negatively influence the final results, especially in cases where a spatial or location variable such as distance to a TOD is the variable of interest. To combat the potential for such bias, we have specified an autoregressive SEM.[2] An SEM controls for omitted spatial influences by factoring in the neighboring residuals into the model estimation. We first specified a spatial weights matrix, whereby each observation is assumed to be influenced by the ten nearest observations to it, weighted by the inverse of distance. This model specification is shown below:

$$\mathrm{Log}(P) = \alpha + \beta_1 T + \beta_2 P + \beta_3 D + \beta_4 N + \varepsilon \quad (3)$$

$$\varepsilon = \lambda \mathrm{W} \varepsilon + \mu \quad (4)$$

where W is the spatial weights matrix, λ is the spatial autoregressive parameter, and μ is the remaining error vector. Estimation of a SEM provides standard coefficient estimates as well as a measure of the spatial error dependence, λ (Anselin, 1988).

Regression Results

We begin by estimating model 1 for all four treatments of the distance variable.

- A – Linear. Assumes a perfectly linear relationship between distance and price in which price changes linearly and monotonically with distance from the station.
- B – Log. Assumes that a non-linear relationship exists, whereby any influences (postive or negative) from the station decline in marginal impact as distance increases
- C – Ring. Three concentric rings are analyzed to see impacts from proximity to the station do not follow any well-specified change over space. Rings at 0–750 m, 750–1250 m, 1250 m+.
- D – Spline. Using the rings above, the spline specification allow for impacts to vary within the rings as well as between them (same ring distances as in C).

Table 3 summarizes the results for model specification 1, distance treatment options A–D. Full model results are shown in the appendix. The linear treatment shows that for each increase of 1 km from the station, prices decrease by approximately 13.8%. The log results show, similarly, that a doubling of distance, say from 1 to 2 km, incurs a 13.9% decrease in price. For the ring model, homes located in the second ring

Table 3. Summary of Base Model Results.

Models 1a–d *Variable*	Linear	Log	Ring	Spline
Distance	−.138	−.139		−.202
Ring 2			−.084	
Ring 3			−.147	
Slope Change in Ring 2				*−.031*
Slope Change in Ring 2				.255
Model diagnostics				
r-squared	.703	.705	.704	.708
Std. error	.195	.194	.197	.194
AIC	−500	−509	−500	−516

Note: Non-significant (.05) coefficient in underlined italics.

(750–1250 m) are worth approximately 8.0%[3] less than those in the nearest ring (0–750 m). Homes in the third ring (1250 m and greater) are worth 13.7%[4] less than those in Ring 1. Interpreting the spline model is not as straightforward. The spline coefficient on Distance indicates that in the first ring, price declines 20.2% for each km away from the station. The change in the slope of the coefficient in Ring 2 means that the change in price as distance increases in Ring 2 is a combination of the −.202 and the −.032, or 23.2%. Slope change in the third ring is then a combination of all three. To better visualize the change in price over distance for the spline model as well as for the other three treatments, Figure 2 shows the simulated value of a standard home under a continuous increase in distance from the TOD based on the results from model 1. Examining the model, diagnostics suggest that as we move from the linear (a) to the spline treatment (d), overall model fit improves sequentially, with the exception of the ring model.

Next, we add neighborhood controls to the model, specifically controlling for land use mix and street connectivity in the area (see Equation (2)). Doing so, has caused the magnitude of the proximity premium (negative effect of distance on price) to increase across all 4 distance treatments (See Table 4). Model diagnostics suggest that all specifications in model 2 provide a better fit than their counterparts in model 1, again with the spline model showing the best fit.

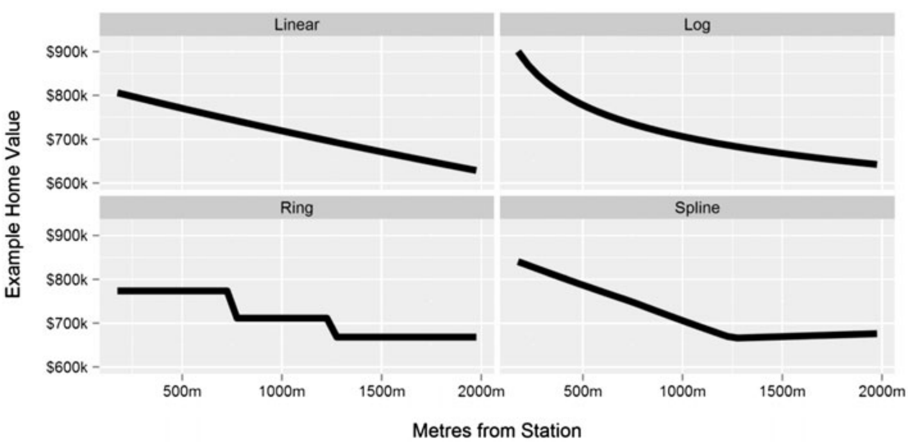

Figure 2. Change in price by distance: model 1.

Table 4. Neighborhood Model Results.

Models 2a–d *Variable*	Linear	Log	Ring	Spline
Distance	−0.181	−.174		−.250
Ring 2			−.091	
Ring 3			−.174	
Slope change in ring 2				*<u>.011</u>*
Slope change in ring 2				.190
Control variables				
Street Connectivity	.039	.037	.033	.034
Land Use Mix	−.045	−.034	*<u>−.023</u>*	*<u>−.031</u>*
Model diagnostics				
r-squared	.709	.710	.707	.712
Std. error	.194	.193	.194	.193
AIC	–520	−527	−512	−528

Note: Non-significant (.05) coefficient in underlined italics

The additional neighborhood control variables have contrasting impacts on home prices. Greater street connectivity shows a price premium, with an increase of 3–4% for each standard deviation increase in street connectivity (due to it being a Z-score). Land use mix, on the other hand, shows a negative relationship with sales prices ranging from insignficant to −4.5%. This negative relationship may be due to the disamenities customarily experienced in locations proximate to non-residential uses such as noise, pollution, congestion, and crime.

To determine if the addition of the neighborhood control variables have adequately captured the spatial variations in the area, we tested the residuals of four estimation of model 2 (2a–d) for spatial autocorrelation using a Moran's I test. In all cases, significant spatial autocorrelation was present. Further testing with a LaGrange Multiplier test showed that the observed spatial dependence was the result of dependence in the error terms and not spatially lagged dependent variables. To correct for this spatial dependence, we then specified a SEM using a spatial weights matrix consisting of the ten nearest neighboring sales, distance-weighted. Analysis of the residuals from the SEM show no statistically significant spatial autocorrelation.

The addition of the spatial error correction vastly improved model performance as indicated by comparing the r-squared, standard errors and AIC values from models 2a–d to models 3a–d (see Tables 4 and 5). Individual coefficient estimates of the four different distance treatments were relatively unaffected by the spatial error correction

Figure 3 illustrates the simulated home prices for an example home across all four distance treatments within each of the three model specifications. Within each model, the strictly linear treatment suggests a significant price premium for home locations near the TOD. Relaxing the strict linearity restraint with the remaining treatments shows that the influence of distance on price declines as distance increases. The spline model, in fact, suggests that influences from the the TOD are only felt up to 1.25 km in distance. For the most part, results from all four distance treatments do not change much over the three different model specification (1–3). This speaks to the relative robustness of the overall model specification even through changes in the handling of additional spatial and locational variables.

The only noticable difference in Figure 3 is that of the estimates from the spline model. The progression from the base model to the SEM for the spline treatment shows

Table 5. Summary of spatial error model results.

Models 3a–d *Variable*	Linear	Log	Ring	Spline
Distance	−.181	−.173		−.267
Ring 2			−.090	
Ring 3			−.157	
Slope change in ring 2				*.034*
Slope change in ring 2				*.178*
Control variables				
Street connectivity	.034	.033	*.025*	.035
Land use mix	*−.031*	*−.021*	*−.001*	*−.024*
Spatial error				
Lambda	.472	.457	.474	.465
Model diagnostics				
r-squared (pseudo)	.758	.759	.757	.759
Std. Error	.173	.173	.173	.173
AIC	−691	−693	−681	−692

Note: Non-significant (.05) coefficient in underlined italics.

when local spatial variation is accounted for via the SEM, that the suggested rise in prices at the farthest distance from the TOD disappears. Looking at the map in Figure 1, this can be explained by the fact that there is a large linear park in the far north of our study area and a school in the far south. Both of these likely exert some influence on home prices, an influence that is only controlled for properly in the SEM.

Discussion and conclusion

We offer two sets of findings from this research; one empirical and one methodological. On the empirical side, our research confirms results found elsewhere in the literature, namely that home prices benefit from proximity to transit stations. This research extends the existing literature to show that this finding is upheld when analyzing a station which has also undergone significant transit-oriented design (TOD).

Overall, while property prices decrease as distance from the TOD increases, this effect dissipates as distance from the TOD increases. This finding is illustrated by the flattening of the price curves in the log, ring, and spline treatements shown in Figure 3. The results align with the expectation that past a certain distance from the TOD, residents would no longer be interested in commuting to the TOD by foot and would find alternative methods to go to their destinations.

We also found significant impacts in a number of models for the neighborhood level variables – street connectivity and land use mix. As expected, properties which had more connections than the average properties are worth more due to the greater accessibility and convenience of having more routing options available. Land use mix, however, had a negative impact on prices indicating that in this area the negative externalities of location near non-residential uses outweighs the benefits. The significance of both neighborhood variables declines signficantly when localized spatial variation is accounted for in our SEM (models 3a–d).

From a methodological standpoint, this research offers two major findings. First, treating distance as a linear spline provides the most flexible method to capture impacts on home prices due to proximity to amenities like a TOD/transit station. The spline

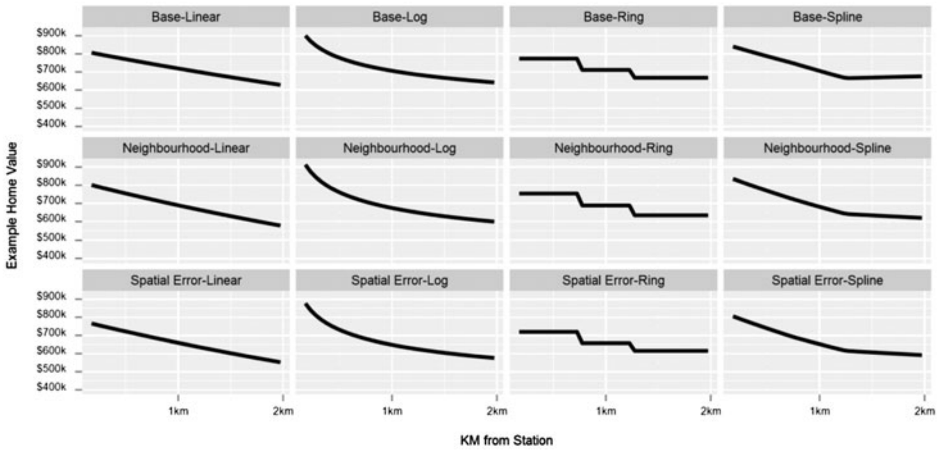

Figure 3. Change in price by distance – all models.

method also produced the best fitting results across all three models and generated a distance-price profile (Figures 1 and 2) that most closely aligns with theory – that of rapidly decreasing benefits to station proximity and then a flattening out of prices after some distance, 1.25 km in this case. As Figure 2 shows, all four distance treatments offer relatively similar results for the first 1250 m; however, after that the models produce varying price expectations. The flexibility of the spline method allows for the model to best fit the existing trends as opposed to a strict linear or log specification.

Next, we see that including neighborhood level variables as well as correcting for spatial autocorrelation in the models help provide more accurate estimates of the impact of TOD proximity on home prices. Particulary noteworthy is the the change in the spline coefficient at distances greater than 1,250 m once the SEM controlled for the amenity impacts of the park (north) and the school (south). In general, properly specifing a model to capture all localized spatial influences on prices can be very difficult and the SEM offers an easier method to account for such factors while allowing for less biased measures of proximity effects.

Nevertheless, there are a few limitations of the data and model used. Firstly, the age of properties or recent renovations are not included. We have attempted to utilize proxy variables to account for these factors, however, the full impacts likely remain expressed in the error terms of the models. Additionally, the distances to the TOD centroid are straight line distances and not actual route distances of the properties to the TOD entrance which would depend on road connectivity. However, it is arguable that this is ‘fair’ for all properties because the train station which is used as the TOD centroid is normally the ‘anchor’ for a TOD and is the main TOD attraction. Therefore, any resident taking the train will have to make their way to the TOD centroid.

Overall, the variables of interest align with previous studies which found that property price decreases as distance from the TOD increases and connectivity increases property prices but property prices are negatively affected when land use mix is excessive. Policy-makers may wish to consider the positive impacts on property values when designing value-capture programs aimed at funding transportation and other neighborhood level improvements as well as when interacting with local residents at initial planning meetings.

Notes

1. Some previous research has used socio-economic variables to control for micro-spatial influences on house prices. We tested the impact of income on prices across all of our models, but found that the influence was minimal and that the spatial error specification did a better job of controlling for potential omitted spatial biases. Due to this, together with the fact that the socioeconomic data cover a time period three to four years prior to our study period has led us to not include the income variable in the final model specifications.
2. A SEM was chosen after testing for spatial autocorrelation (present in all cases) and then running a LaGrange Multiplier test on the results from model 2. In all cases, the LaGrange test results indicated that the spatial dependence in the model was due to spatial error and not spatial lags (which would have necessitated a spatial lag model).
3. The raw coefficient value of a dummy variable in a semi-log regression model must be transformed by the formula exp(c)-1 to convert to a true percentage impact as explained by Halvorsen and Palmquist (1980).
4. Ibid.

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Appendix 1

Full Model Results

Base models Models 1a–d	Linear – Coef	Linear – SE	Log – Coef	Log – SE	Ring – Coef	Ring – SE	Spline – Coef	Spline – SE
Lot size	.053	.003	.053	.003	.054	.003	.053	.003
Beds	.065	.008	.065	.008	.065	.008	.065	.008
Baths	.088	.011	.088	.011	.088	.011	.087	.011
Garage	.037	.017	.035	.017	.035	.017	.035	.017
Walk-in wardrobe	.07	.019	.072	.019	.077	.019	.074	.019
Study	.037	.014	.037	.014	.036	.014	.038	.014
Townhouse	−.153	.019	−.152	.019	−.147	.019	−.149	.019
Dist to TOD	−.138	.014	−.139	.014			−.202	.072
Ring 2					−.084	.015		
Ring 3					−.147	.015		
Ring 2 spline							<u>*−.032*</u>	<u>*.099*</u>
Ring 3 spline							.255	.07
Time fixed effects								

Note: Non-significant (.05) coefficient in underlined italics.

Base models + neighborhood variables								
Models 2a–d	Linear – Coef	Linear – SE	Log – Coef	Log – SE	Ring – Coef	Ring – SE	Spline – Coef	Spline – SE
Lot size	.054	.003	.054	.003	.054	.003	.054	.003
Beds	.065	.008	.064	.008	.064	.008	.065	.008
Baths	.086	.011	.086	.011	.087	.011	.086	.011
Garage	.041	.017	.039	.017	.04	.017	.04	.017
Walk-in wardrobe	.064	.019	.067	.019	.072	.019	.068	.019
Study	.036	.014	.035	.014	.035	.014	.036	.014
Townhouse	−.148	.019	−.146	.019	−.14	.019	−.145	.019
Dist to TOD	−.181	.017	−.174	.016			−.25	.073
Ring 2					−.091	.015		
Ring 3					−.174	.017		
Ring 2 spline							*.012*	*.1*
Ring 3 spline							.19	.072
Street connectivity	.039	.009	.037	.009	.033	.009	.034	.009
Land use mix	−.045	.016	−.034	.015	*−.023*	*.016*	*−.031*	*.017*
Time fixed effects								

Note: Non-significant (.05) coefficient in underlined italics.

Spatial Error Models Models 3a–d	Linear – Coef	Linear – SE	Log – Coef	Log – SE	Ring – Coef	Ring – SE	Spline – Coef	Spline – SE
Lot size	.053	.002	.053	.002	.054	.002	.053	.002
Beds	.056	.007	.056	.007	.056	.007	.056	.007
Baths	.1	.01	.1	.01	.1	.01	.1	.01
Garage	.036	.016	.035	.016	.035	.016	.036	.015
Walk-in wardrobe	.052	.017	.053	.017	.056	.017	.053	.017
Study	.032	.012	.032	.012	.032	.012	.033	.012
Townhouse	−.148	.018	−.148	.018	−.145	.018	−.147	.018
Dist to TOD	−.181	.027	−.173	.027			−.267	.115
Ring 2					−.09	.023		
Ring 3					−.157	.026		
Ring 2 spline							*.034*	*.157*
Ring 3 spline							*.179*	*.114*
Street connectivity	.034	.013	.033	.013	*.025*	*.013*	.031	.013
Land use mix	*−.031*	*.025*	*−.021*	*.024*	*−.001*	*.025*	*−.018*	*.025*
Time fixed effects								

Note: Non-significant (.05) Coefficient in Underlined Italics.