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Spatial-difference-in-differences models for impact of new mass rapid transit line on private housing values

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A B S T R A C T

This study uses the opening of the new Circle Line (CCL) in Singapore as a natural experiment to test the effects of urban rail transit networks on non-landed private housing values. We use a network distance measure and a local-polynomial-regression approach to identify the CCL impact zone with discontinuity in housing price gradient between a treatment zone and a control zone. We then estimate the spatial difference-in-differences models that account for spatial autocorrelation in housing price changes in the two zones "before and after" the opening of the CCL. We find that the opening of the CCL increases housing value in the treated neighborhoods located within the 600-metre network distance from the new CCL stations by approximately 8.6%, relative to other properties in the untreated neighborhoods controlling for heterogeneities in housing attributes and local amenities, and spatial and temporal fixed effects. We find significant "anticipation" effects as early as 1 year prior to the opening of the CCL line, but the effects diminish closer to the actual opening date. The results imply that the inter-dependent spatial structure between the treated and the untreated neighborhoods, if neglected, may lead to over-estimation of the capitalization effects of the new transit lines on housing values.

1. Introduction

An efficient and environmentally friendly urban rail transit system (RTS) has become an important part of urban infrastructure in today's cities to address urban transport challenges. Governments of many developed and developing countries have invested a huge sum of public money to build new and/or expand existing urban RTSs in their major cities (Suzuki et al., 2013). New RTS lines improve connectivity and bring agglomeration to the city centre; and as a city grows, economic externalities could spill over through extending the RTS lines to other areas outside the city (Chatman and Noland, 2014). New RTS investments help narrow the rental gaps between the city centre and the outlying areas, and as a result, flatten the bid-rent gradient (McMillen and McDonald, 2004; Zheng and Kahn, 2008).

There are other social and economic costs and benefits associated with new RTS lines. A "*substitution*" effect between road and RTS transport modes is created, if some private car owners switch to urban RTS when commuting to city centres (Baum-Snow and Kahn, 2000). When more public road users switch to RTS, public road users could enjoy shorter travelling time on less congested roads and reap significant reduction in marginal social costs. In addition, environmental quality is also improved through the reduction in greenhouse gas emissions by users who switch from private cars and public buses to RTS.

The accessibility benefits of a RTS are local by nature. People who live near transit stations are more likely to use the urban RTS for commuting purposes. Therefore, we expect variations in housing prices between areas that are within and those that are outside the accessibility range of RTS stations. Many studies have found empirical evidence of positive capitalization effects of proximity convenience associated with new urban RTS stations on housing prices.[1] However, these studies, which usually capture capitalization effects of RTS with a distance variable (either discrete or continuous) in the standard OLS hedonic housing price model, are vulnerable to the problems relating to omitted variables and endogeneity in housing prices and distances to RTS stations. Some of these problems are spatial by nature. This paper applies three innovations in spatial statistical tools to improve the quasi-experiment approach in capitalizing the RTS effects.

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[1] Evidence of positive capitalization effects of urban rail transit systems is shown in many studies across different countries, which include studies in major US cities (non-exhaustive), such as Washington DC (Damm et al., 1980), Atlanta (Nelson, 1992; Bowes and Ihlanfeldt, 2001), Miami (Gatzlaff and Smith, 1993), Chicago (McDonald and Osuji, 1995; McMillen and McDonald, 2004), San Francisco (Landis et al., 1995), and other cities such as Toronto (Bajic, 1983; Dewees, 1976), Taipei (Lin and Hwang, 2003), Seoul, (Bae et al., 2003), London (Gibbons and Machin, 2005) and the Netherlands (Amsterdam, Rotterdam and Enschede) (Debrezion et al., 2011).

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First, most studies use either a Euclidean distance (Baum-Snow and Kahn, 2000; Chalermpong, 2007, and others), or a Euclidean distance-based ring buffer (Lin and Hwang, 2003; Des Rosiers et al., 2010; Dubé et al., 2011; and others) to identify the treatment zone with respect to the nearest RTS stations. At the local level, RTS stations are not usually surrounded by lands with flat and plain topographies. Instead, they are sometimes criss-crossed by major road networks, divided by rivers, and obstructed by other buildings. The diverse spatial and topographic features could be potential sources of measurement errors, especially in densely built-up urban cities. Incorrect distance measures, if used indiscriminately without adjustments, could distort the pricing of RTS accessibility premiums. In this study, we use a network-based distance measure to capture the shortest route (network distance) between a house and the nearest RTS station based on the local road network map. The network walking distance to the nearest RTS stations is a more realistic and direct way of capturing users' marginal willingness to pay (MWTP) in housing prices.

Second, the delineation of treatment zone remains a challenge for researchers who use the difference-in-differences (diff-in-diff) approach to assess the treatment effect of new RTS lines. Furthermore, the supply inelasticity imposed by the shortage of developable lands near RTS stations may create, in equilibrium, disproportional price responses to increased demand in the area. We apply the local polynomial regression (LPR), which is a spatial innovation used in Linden and Rockoff (2008), to fit housing prices on distances to RTS stations with a locally weighted least squares estimator. The LPR allows for non-linear capitalization effects, which are likely to be stronger in areas near the new RTS stations where housing supply is highly inelastic. Based on the LPR, we identify the treatment zone of RTS that shows discontinuity in housing price gradients between a treatment and a control zone, so that the diff-in-diff analysis can be more accurately performed.

Third, while most residents could not influence and vote on, in most instances, the location of a new rail transit station, they could, however, vote with their feet by moving close to a RTS station in the neighborhood. Families that have a high MWTP for the RTS accessibility buy houses from families who stay near RTS stations, and yet have relatively low MWTP for the RTS services. These new families move in and displace the existing families from the RTS neighborhoods. They create a different form of social network for the treatment area over time. The new RTS line attracts new local amenities and other commercial activities into the neighborhood. The spatial dynamics of the treatment neighborhoods near a new RTS line could be different from the (control) neighborhoods not served by a RTS line. The standard difference-in-differences (diff-in-diff) approach that assumes constant spatial attributes in the treatment and control areas before and after the treatment could over-estimate the capitalization effects associated with the opening of new rail transit stations. We incorporate the dynamic and spatially dependent treatment effects by adding spatial-autoregressive lag and error terms into our diff-in-diff housing price models (Anselin, 1988).

The Mass Rapid Transit (MRT) system is a rail-based transit system, which started running in 1987, and it forms the backbone of the public transport system in Singapore. The MRT network has been expanded over the years with additions of new lines and stations to meet the growing commuter demand. In this study, we use the opening of the new Circle Line (CCL), the fourth line on the MRT network in Singapore, as a quasi-natural experiment, and apply spatial-dependence diff-in-diff models to evaluate the capitalization effects of the CCL on non-landed private housing values.

Using the same LPR model as in Linden and Rockoff (2008), we identify the area within 600 meters (m) by the network distance from the closest new CCL stations as the impact (treatment) zone. We sort the housing samples into a treatment group, if the shortest network distance between houses and the closest CCL stations falls within 600 m; and otherwise, into a control group. The treatment effects, which show the price premiums for non-landed private houses in the treated zone relative to the control zone "before and after" the opening of the new CCL, are estimated at 10.6% after controlling for housing characteristics, local amenities, spatial and temporal fixed effects. However, when the inter-zone spatial dependence structure is added to the spatial diff-in-diff (SDID) model, we find significant, but weaker treatment effects of 8.6% for the treated houses relative to the untreated houses.

Based on the 3755 non-landed houses in the treatment zone transacted after the opening of new CCL stations with an aggregate value of S$4.42 billion,[2] the treatment effects of the new CCL opening are translated into marginal *willingness to pay* for housing of approximately S$380.12 million. For housing buyers, the findings show the importance of understanding spatial variations and dynamics when capitalizing RTS effects into housing values. For urban and transport planners, they should be mindful of local features and land supply constraints when designing transportation policy and value capture programs.

This paper is organized as follows. Section 2 reviews related literature in the study of the relationships of RTS locations and housing values. Section 3 provides a brief overview of the housing market and the MRT network in Singapore as background information. Section 4 describes the data and empirical methodology. The Section shows graphical evidence on the impact of the CCL using the local-polynomial-regression analysis, and discusses the identification strategy. Section 5 presents and discusses the empirical results. Section 6 concludes the paper.

2. Literature review

Alonso (1964), Muth (1969) and Mills (1972) argue that households trade-off between commuting cost and housing consumptions in their residential location decisions. This is the fundamental premise for the monocentric city model that predicts a negative housing price gradient with respects to distance (transportation cost) to the employment centre. The negative price-distance relationship, which is known as the bid rent curve in the urban economics literature, has significantly shaped the urban landscape, and influenced spatial distributions of households and firms across a city. Many empirical studies have shown that new urban RTS infrastructure investments could significantly flatten the bid rent gradient, and reduce the housing price gap between urban and rural areas (Nelson, 1992; Gatzlaff and Smith, 1993; Landis et al., 1995; McDonald and Osuji, 1995; Bowes and Ihlanfeldt, 2001; McMillen and McDonald, 2004; and others). Increased accessibility brought by new RTS investments is translated into housing wealth accrued to local residents via the capitalization of the RTS line effects (Edel and Sclar, 1974; Hilber and Mayer, 2009; Diao et al., 2017).

A large number of empirical studies has found evidence of positive capitalization effects of proximity to RTS stations in housing values (Gibbons and Machin, 2005; Hess and Almeida, 2007; Diao and Ferreira, 2010; Diao, 2015; among others). Debrezion et al. (2007) provide a meta-analysis of 57 cities and suggest that property values increase by 2.3% every 250 m closer to a railway station. There are also other studies that find insignificant, or in some cases, even negative effects of the proximity to selected RTS stations in some cities (e.g., Gatzlaff and Smith, 1993; Landis et al., 1995). The negative externalities are usually caused by noise and high crime rates found in areas near RTS stations (Bowes and Ihlanfeldt, 2001, Diao et al., 2016).

Most of the early studies use a Euclidean distance measure to the closest RTS station, which is represented either by a discrete or a continuous variable in standard hedonic models, to capture cross-sectional variations in housing prices (e.g., Coffman and Gregson, 1998; Bowes and Ihlanfeldt, 2001; Hess and Almeida, 2007; Diao and

[2] 1 US$ = 1.267S$ as on 31 December 2013 (Source: finance.Yahoo.com).

Ferreira, 2010). Compared to Euclidean distance, network distance is a more realistic measure taking into account natural obstacles (rivers, canals, and parks) and spatial constraints (existing buildings and rail tracks) in local areas.

The popular Rosen's hedonic housing price models (Rosen, 1974), despite having a rich set of housing and spatial attributes, face serious endogeneity issues when applied to study the RTS effects. The models are not able to separate unobserved factors that could influence the covariance between housing price and RTS accessibility. Some researchers use the repeated sales data to control for the endogeneity effects between unobserved factors and urban RTS in modelling housing price changes (e.g., McMillen and McDonald, 2004; Billings, 2011; Chatman et al., 2012; Dubé et al., 2013; Kim and Lahr, 2014; Sun et al., 2015). The repeated-sales approach removes biases caused by time-invariant omitted variables by taking the first differencing in housing prices. The basic idea is to regress price changes on a time vector that corresponds to the periods between consecutive sales of the same house, and keep the hedonic attributes of the same house and its surrounding neighborhood characteristics constant. Price changes, if observed, must be correlated with a new RTS line opening that falls within the repeated sale periods. By limiting the sample to only houses that sell at least twice, the sample is significantly reduced. In the sample selection process, biases may arise because houses that are sold twice or multiple times are likely to have different attributes from those that sell only once (Gatzlaff and Haurin, 1997).

Changes in structural characteristics and/or (dis)amenities in local areas sometimes occur over a long period of time, and sometimes randomly, thus differencing the repeated housing prices alone could not adequately remove inter-temporal effects of both observed and unobserved factors. In recent years, a quasi-experimental approach has become increasingly popular among researchers in the regional and urban economics literature (Gibbons and Machin, 2005; Billings, 2011; Diao et al., 2017). In a randomized experiment, sample houses are sorted into a treatment group and a control group based on the proximity to RTS stations, and a random event, such as the opening of new RTS stations, is used to create exogenous shocks to housing prices. The diff-in-diff models are estimated to test the effects on before-and-after price changes between a treatment group (an affected area) and a control group (an unaffected area) following the exogenous shock, controlling for observed and unobserved variations in housing and spatial attributes. If the pre-existing between-the-group price variations change after the treatment, the causality of new RTS stations on housing prices could be established in the local areas.

In the diff-in-diff models, defining the treatment area using proximity measures (such as linear distance or buffer zone) is subject to omitted variable problems, especially when the selection of the RTS station location is not exogenous. For instance, central planners are more likely to put a RTS station in high density city centres than in sparsely populated rural areas, *ceteris paribus*. The RTS effects in a densely populated city centre co-vary closely with other amenities in the areas. Other cofounders such as shopping facilities that are attracted to areas near RTS stations could also influence preferences for housing that are close to RTS stations. It would be difficult to measure house buyers' MWTP for the RTS accessibility. Facing the same challenges in the study of negative externalities of living close to convicted criminals, Linden and Rockoff (2008) use a local polynomial regression approach to identify the treatment effects weighted by the moving-in and location of a sex offender's house in a neighborhood. Haninger et al. (2017) use the same approach to study the impact of brownfield remediation; and Muehlenbachs et al. (2015) study the impact of shale gas developments on property values. We use for the first time this spatial innovation to study how the opening of new MRT line in Singapore would impact housing values in the areas near the new MRT stations.

However, in areas undergoing dynamic changes following the opening of new RTS stations, there is a need to control for possible auto-regressive lag and error in spatial interactions of houses (Anselin, 1988). The application of the state-of-the-art spatial-econometric techniques has attracted strong interest in recent years. For examples, Chagas et al. (2016) use the spatial-dependence diff-in-diff (SDID) to study sugarcane production and health. Brasington et al. (2016) use the spatial autoregressive lag multinomial logit model to study school enrolment choice. Heckert and Mennis (2012) apply the SDID models to measure the impact of innovative vacant land greening programs on residential property values in Philadelphia. Dube et al. (2014), which is the closest to our study, use the SDID to study impact of public mass transit system expansion on real estate values in Montreal, Canada, though they found insignificant treatment effects in the results. In this study, we calibrate SDID models to estimate the capitalization effect of a new MRT line in Singapore, accounting for the spatial dependencies in the dependent variable and the error term.

3. Urban rail transit network in Singapore

Singapore is an island-state with a land area of approximately 714 square kilometres (km^2).[3] Recognizing the physical constraints for building more roads, the Singapore government has conducted a series of feasibility studies since 1967 on the construction of a new rail transit system to alleviate traffic congestion problems. The Parliament finally approved the massive MRT project in 1982, which was estimated to cost about S$5.3 billion (in 1982 dollars). The initial phase of the MRT system comprises the 67-kilometre (km) North-South Line (NSL) and the East-West line (EWL). These two lines, with a total of 42 stations, form the backbone of Singapore's MRT system today. Construction works for the proposed MRT system started in October 1983. A 6-km stretch of the NSL running from Yio Chu Kang to Toa Payoh first opened in 1987. The two MRT lines were fully completed and in operation only in July 1990.

Singapore's government continues to expand the MRT network by adding new MRT lines and more stations to meet the growing commuter demand. In 2003, the new Northeast Line (NEL) with 16 stations and a total track length of 20 km was added to the MRT network. The Circle Line (CCL) is Singapore's fourth MRT line, which opened in three stages between 2009 and 2012:

- Phase 1: 28 May 2009: (Bartley - Marymount)
- Phase 2: 17 April 2010: (Dhoby Ghaut - Bartley) (Eastern stretch)
- Phase 3: 8 October 2011: (Marymount – Harbour Front) (Western stretch)

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The 35.7 km CCL is a ring-shaped line connecting the three existing lines at 6 different interchanges (Fig. 1). The new CCL extension, joining the Marina Bay station to a new Promenade station on the CCL line, was added and opened on January 14, 2012. By 2014, the MRT network coverage consisted of 154.2 km MRT rail line and 106 MRT stations. The annual daily ridership for the MRT system is estimated at 2,879,000 in 2015.[4] The government unveiled the 2013 Land Transport Master Plan (LTMP) with a long-term plan to double the current MRT network to 360 km by 2030. Two new rail lines, which are the Cross Island Line (CRL) and Jurong Region Line (JRL) will be built, and extensions to the Circle Line (CCL), North East Line (NEL) and the Downtown Line (DTL) are also planned to improve connectivity of the MRT system. By then, eight out of ten households in Singapore will be able to access the nearest MRT station within a 10-minute walk. Singapore will surpass the current rail length in Tokyo (304 km) and Hong Kong (218 km) upon the completion of the

[3] Source: Singapore Department of Statistics.

[4] Singapore Land Transport: Statistics in Brief 2015. Source: Land Transport Authority.

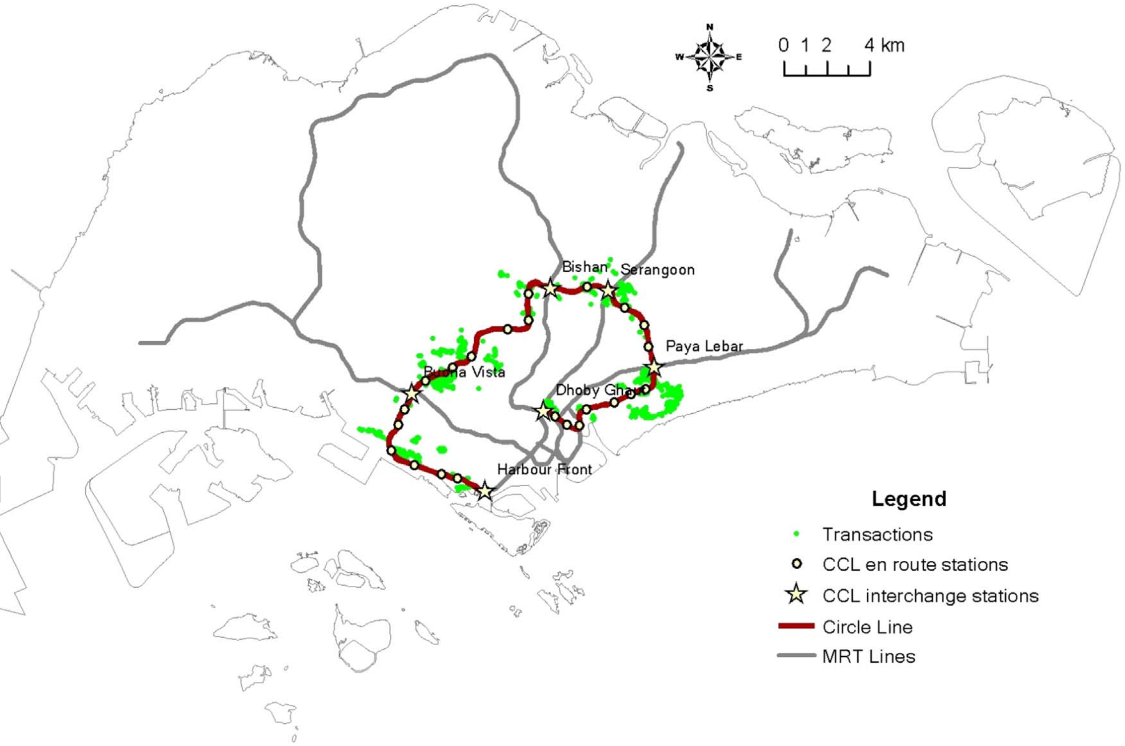

Fig. 1. MRT Network and Non-Landed Private Housing Transactions. Note: The Figure shows the map of Singapore, and the darken solid (red line) shows the Circle line MRT stations on the line are represented by dot (en-route stations) and star (interchange stations); and the light green dot represent the distributions of housing samples along the Circle Line.

planned MRT networks.[5] Table 1 shows the existing and the proposed MRT lines.

4. Data and empirical design

4.1. Data sources

Singapore has a unique two-tiered housing market with a dominant public housing market coexisting with a private housing market, which operates like any other *laisse-faire* markets.[6] As of 2016, the private housing stocks constitute about 27% of the total housing stock[7] (about 372,462 units based on 1Q2016 statistics)[8]; and 73.96% of the private housing stock is made up of non-landed housing types, which include executive condominiums (EC), apartments, and condominiums. We use only the non-landed housing samples in our analysis[9]; and they are identified by the three property type dummies: "apartment" (37.1%), "condominium" (62.3%) and "executive condominium" (0.6%).

We obtain the transaction data from the "Realis" database, a real estate information system managed by the Urban Redevelopment Authority (URA) covering the 6-year period from April 2007 to March 2013. The data contain the detailed records of non-landed private housing transactions in Singapore, which include transaction price, transaction date, street address, postal code, and various attributes of properties including floor area, floor level, property type, property lease type, purchaser type, and sale type. Table 2 presents the descriptive statistics, which include mean (in Column 2) and standard deviation, (S.D.) (in Column 3) of the key variables for the full sample. The average price of the housing sample is estimated at S$1,402,168 (US$1,106,684), or an equivalent of S$12,234 per square meter (S $/psm) (US$9,656 psm). The average floor area is about 103.5 sqm (or "*ln Floor Area*" of 4.640) and the average floor level of 7.8 reflects the high-density living characteristics in Singapore. By land tenure type, 51.2% of the housing samples are built on "Freehold" lands, and the remaining 48.8% of the housing samples on the "Leasehold" lands with a typical 99-year lease. The purchaser type is sorted based on his/her current address into "HDB" (32.3%), if a purchaser lives in a public flat; and "Private" (67.7%), if a purchaser lives in a private apartment. The housing data are also grouped by the sale type into three categories: "Newsale" indicates a pre-completion housing sale by developers (51.2%); "Subsale" indicates a housing unit sold by an individual owner before completion (8.2%); and "Resale" indicates a completed housing unit sold by an individual owner in the secondary markets (40.6%).

Each transacted property is geocoded based on a unique 6-digit postal code using geographic information systems (GIS) tools. For the purpose of mitigating possible boundary discontinuity problems, we demarcate the study area by a 1.6 km radius from CCL stations, and retain a total sample of 21,954 non-landed private housing transactions for our analysis. The sample housing transactions are represented by the green dots in Fig. 1. We conduct robustness tests by expanding the study areas to 2.0 km radius from the CCL stations. For each of the geocoded housing samples, we measure the distances to various local amenities, including the CBD, top primary schools, major shopping malls, bus stops, and the expressway, and control these factors in the regression. The summary statistics for the spatial variables are summarized in Table 2.

4.2. Network distance measures

The monocentric city model assumes that urban lands have plain and smooth terrain, on which different land uses are uniformly

[5] Source: LTA, Land Transport Master Plan 2013.

[6] During the study period, the average unit price for non-landed private houses along the CCL corridor is estimated at S$12,234 psm, compared to the average of S$4,180 psm for resale public housing flats.

[7] Source: Lee, U-Wen, "Proportion of private homes grows to 27%," Business Times, 9 May 2017.

[8] Source: The Realis database, Urban Redevelopment Authority (URA), Singapore.

[9] The volume of landed housing transactions near the CCL MRT stations is small and thus excluded from the study. Households living in the landed houses are mainly high-income families with a high level of car dependency, and their MWTP for the MRT services is expected to be small relative to the prices of their landed houses.

Table 1
Existing and planned MRT lines in Singapore.

MRT Line	Operator	MRT Line in Operation			Under Construction and Planning			Total length (km)
		Number of Station	Length (km)	Commencement	Number of station	Length (km)	Commencement	
North South Line	SMRT Trains	26	44.7	11/7/1987	1	0	2019	44.7
East West Line	SMRT Trains	31	49.7	12/12/1987	4	7.5	2017 (Tuas West Extension)	57.2
Northeast Line	SBS Transit	16	20	6/20/2003	1	2	2030	22
Circle Line	SMRT Trains	30	35.4	5/28/2009				35.4
Downtown Line	SBS Transit	18	20.9	12/22/2013	18	23.2	2017 (Stage 3) / 2024[a]	44.1
Thomson-East Cost Line	TBA				31	43	2019[a]	43
Cross Island Line	TBA				–	50	2030[a]	50
Jurong Regional Line	TBA				–	20	2025[a]	20
Total		121	170.7		55	145.7		316.4

Notes: The table summarizes the details of the MRT lines in operation, under construction and planning in Singapore. The data are obtained from various sources including LTA, Wikipedia, and newspapers.

[a] represents the opening year of the first stage of corresponding MRT line, based on projects.

Table 2
Descriptive statistics.

	Full Sample		**Treatment Group**		**Control Group**		**Linear group**	
			Network Distance ≤600 m		Network Distance > 600 m		Linear Distance ≤600 m	
Observation	21,954		7,388		14,566		15,429	
	Mean	S.D.	Mean	S. D.	Mean	S. D.	Mean	S.D.
Price per housing unit (S$)	1,402,168	985,590	1,192,170	620,144	1,512,530	1,111,137	1,358,329	994,618
Price per square metre (S$/m^2)	12,234	3,971	11,693	3,361	12,509	4,220	12,349	4,088
Ln Price	13.999	0.552	13.895	0.435	14.05	0.596	13.967	0.543
Ln Floor Area	4.640	0.492	4.572	0.435	4.674	0.515	4.601	0.487
Floor Level	7.799	6.151	8.950	6.275	7.215	6.003	8.027	6.429
Property Type								
Apartment	0.371	0.483	0.397	0.489	0.357	0.479	0.401	0.490
Condominium	0.623	0.485	0.603	0.489	0.633	0.482	0.590	0.492
Executive Condominium	0.006	0.078	0.000	0.000	0.009	0.096	0.009	0.093
Lease Type								
Freehold	0.512	0.500	0.349	0.477	0.595	0.491	0.477	0.499
Leasehold	0.488	0.500	0.651	0.477	0.405	0.491	0.523	0.499
Purchaser Type								
HDB	0.323	0.468	0.342	0.475	0.313	0.464	0.333	0.471
Private	0.677	0.468	0.658	0.475	0.687	0.464	0.667	0.471
Sale Type								
New Sale	0.512	0.500	0.534	0.499	0.500	0.500	0.535	0.499
Sub Sale	0.082	0.275	0.088	0.284	0.079	0.270	0.075	0.264
Resale	0.406	0.491	0.378	0.485	0.420	0.494	0.390	0.488
Network Distance to MRT (m)	803.193	397.163	376.064	149.674	1,019.836	294.805	626.568	311.164
Euclidean Distance to MRT (m)	490.773	309.308	219.997	111.977	628.113	285.983	320.653	151.716
Distance to School (m)	1,667.153	688.148	1,528.906	702.179	1,737.273	670.130	1,576.231	655.794
Distance to CBD (m)	6,014.183	1,647.860	6,280.275	1,509.667	5,879.219	1,697.882	5,934.527	1,691.017
Distance to Expressway (m)	1,111.423	663.418	1,091.656	553.056	1121.449	712.70	1,141.424	594.320
Distance to Bus Stop (m)	157.840	97.852	135.459	67.821	169.192	108.556	163.027	97.807
Distance to Mall (m)	1,834.797	880.697	1900.909	895.742	1,801.264	871.082	1,830.326	915.378

Note: The table shows the descriptive statistics (means and standard deviation (S.D.)) for the full sample, the treatment (≤600 m) and the control sub-sample (> 600 m), based on the network distance measures, and the sub-sample based on linear distance of ≤ 600 m. The data contain the price variables, housing attributes, lease type, sale type, distance measures and other spatial attributes.

distributed from the city centre to the rural areas. The land supply in a monocentric city is mainly, if not solely, governed by zoning and density controls. The "*man-made*" controls influence prices in local real estate markets. Saiz (2008) shows that the regulatory controls are endogenous, and highly dependent on the geography and topography of a city. Based on the satellite-based land use data provided by the United States Geographic Service (USGS), he shows that the land supply elasticity is severely constrained by spatial and topographical features, such as elevated terrains and water bodies. Therefore, the most widely used Euclidean measure of distance to the nearest RTS/ MRT stations, which ignore spatial and topographical constraints, could distort the estimation of housing price premiums.

Fig. 2 uses a sample house located at 107 Aljunied Crescent (postal code 280107) to illustrate the differences between the Euclidean distance (dotted line) and the network-distance (darkened line) measured with reference to the nearest MacPherson MRT Station

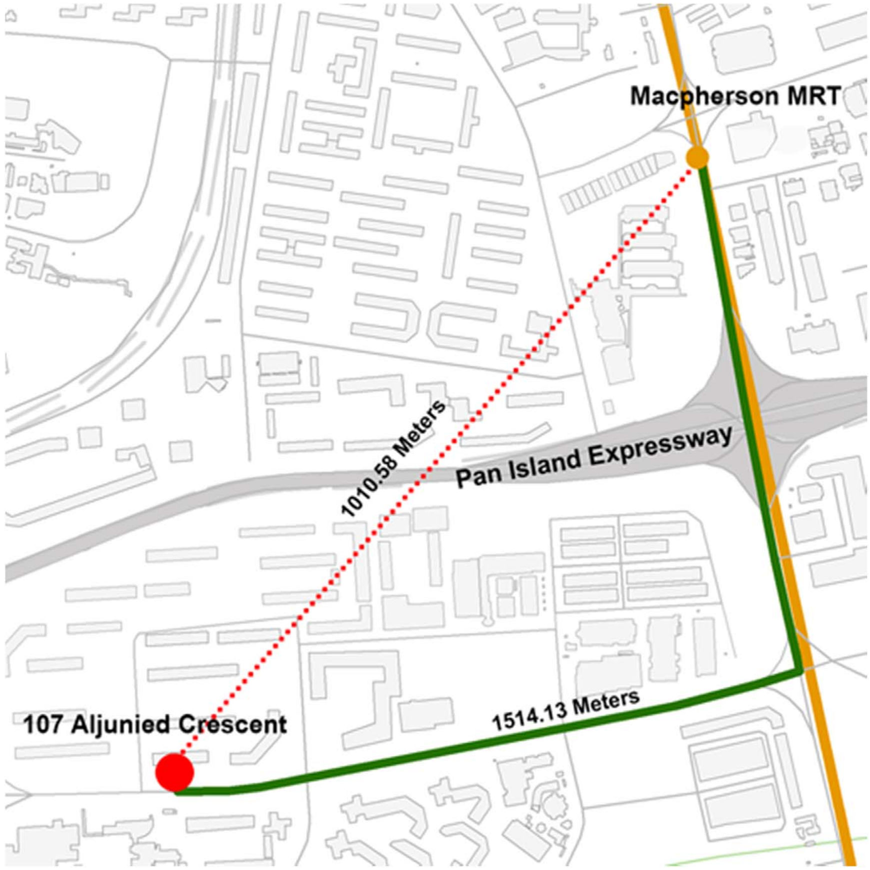

Fig. 2. Network distance and Euclidean distance. Note: The figure uses a sample house located at 107 Aljunied Crescent to illustrate the different between the Euclidean distance (dotted line) and the network distance (solid green line) to the closest MacPherson MRT Station.

(postal code 409048). The sample house is separated by the Pan Island Expressway; and if the spatial constraint that hinders the direct access to the MRT station were ignored, we obtain the Euclidean distance of 1,010.58 m to the MRT station. The Euclidean distance is a simple, but impractical measure on the ground, because it is not possible for the owner of the sample house to cross the expressway and walk to the MRT station. The owner is likely to use the shortest route as indicated by the darkened line, which is measured at 1,514.13 m, to go from his/her house to the MRT station. Therefore, a proximity measure without considering spatial features and the actual configuration of road networks is subject to measurement errors; and if used indiscriminately, could result in biased estimation.

This study is probably one of the few in the urban literature that uses the network-based distance to measure the distance of a sample house to the nearest CCL MRT station. We overlay the road network layer obtained from the Singapore Land Authority (SLA) onto the base layer of geospatial data of housing sale and MRT station locations. Using GIS tools, we simulate the shortest route (or known as the network distance) for a sample homeowner to walk to the nearest MRT station taking various obstacles, such as expressway and water bodies, into considerations. For the full housing samples, the shortest network distance to the nearest CCL MRT stations adjusting for spatial and topographical constraints is estimated at 803.19 m, on average, which is significantly larger than the average Euclidean distance of 490.77 m for the same sample.

4.3. Local polynomial regression (LPR) and treatment zone

Previous transport studies often use a discretely defined buffer zone of 400 m from the transit stations to demarcate the catchment (treatment) area, because the 400 m is deemed a reasonable walkable distance for people (Untermann, 1984). The walkable distance, however, could be influenced by many factors, such as weather, culture, pedestrian walkways and infrastructure, among others. In addition, there are also possible cofounders, both cross-sectionally and temporally, that could influence housing prices near the MRT stations. Owners, who live close to MRT stations, may trade off accessibility benefits against other negative externalities, such as noise, traffic congestion, and loss of exclusivity in the living environment. The MWTP of owners for the MRT accessibility benefits is expected to decrease disproportionally with the distance to the stations and the new CCL station capitalization effects are expected to dissipate from housing values after a certain cut-off distance. Therefore, studies that discretely impose a discontinuity on a treatment zone using a binary dummy may be subject to possible identification errors, for example, sorting two adjacent terrace houses into the treatment and the control group.

In the study of criminals, Linden and Rockoff (2008) find that localized dis-amenities are created when a sex offender moves into a neighborhood, but the effect dissipates quickly with the distance from the criminal's house. They model the effect of neighborhood dis-amenities at the local level as a non-linear smoothing function in a LPR,[10] and find significant differences in the pre-existing and the post-arrival price trends for houses located within 0.1 miles, and those located between 0.1 and 0.3 miles, after the arrival of sex-offenders into the neighborhood. In our quasi-experiment setup, we use the LPR approach to identify differential (non-linear) treatment effects on houses located in a small localized area surrounding MRT stations.

[10] LPR is a nonparametric technique to estimate bivariate relations of two variables using a subset of the data, to produce a smooth curve point by point.

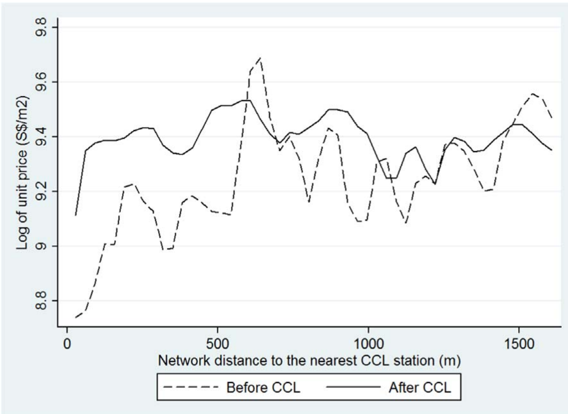

Fig. 3. *Change of housing price gradients of network distance to CCL stations before and after CCL in operation.* Note: The figure plots the log-housing price per square meter (S$/psm) against the network distance to the closest MRT stations. The solid line represents the housing price gradient after the CCL opening, and the dashed line represent housing price gradient before the CCL opening.

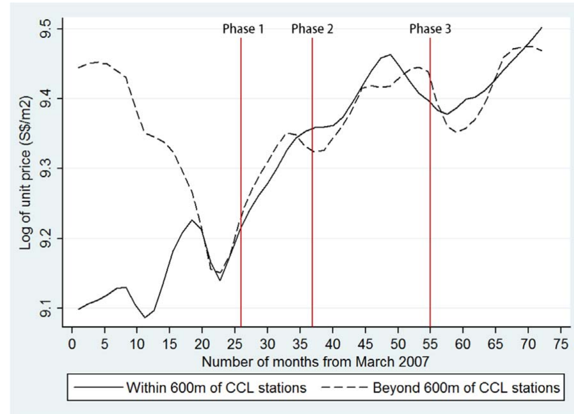

Fig. 4. *Temporal changes of unit price in the treatment and control zones.* Note: the Figure plots the price gradients (by log-unit housing price) for the two sets of sample houses, which include the treatment sample (within 600 m from the CCL stations) (solid line) and the control sample (beyond 600 m from the CCL stations) (dashed line), over time (by month from March 2007) (represented by the X-axis). The three vertical lines represent the opening of the CCL in three different phases.

4.3.1. Graphical evidence

Based on the LPR, we plot price gradients "before" and "after" the opening of the CCL line with respect to network distance to the closest CCL MRT stations in Fig. 3. The x-axis is the network distance to CCL stations, and the y-axis is the logarithm of inflation-adjusted housing price per m^2 adjusted for housing size and inflation. The darkened line shows the post-CCL opening price gradients in a range of between S $9,897 psm and S$13,360 psm (Ln Unit Price = 9.2 and 9.5) distributing across the neighborhood demarcated by a 1600 m radius from the closest CCL stations. The pre-CCL opening price gradient as represented by the dashed line shows lower housing prices of the pre-CCL periods relative to the post-CCL prices, except for the two areas between 600 m and 700 m and also above 1500 m. If the new CCL stations were viewed as positive amenities, we expect buyers to pay premiums for houses that are located close to the MRT stations.

Based on the price changes before and after the CCL opening as indicated by the gap between the darken line and the dashed line, we find strong price increases for houses located within 600 m network distance to CCL stations compared to price changes for houses outside the 600 m region. The pre- and post-CCL price effects appear to be non-linear in the small area subject to the treatment of the CCL line. Fig. 3 suggests that the 600 m network distance to the nearest MRT station is an appropriate cut-off distance to define the impact zone of new CCL stations. The unit price increase in the impact zone after the CCL opening provides some graphical evidences that suggest a causal impact of new CCL stations on non-landed private housing values in the neighboring areas. We use the 600 m cut-off (network) distance to sort the sample houses into a treatment group with direct accessibility benefits from CCL lines, and a control group that is indifferent to the opening of the new CCL line. We then estimate the diff-in-diff models to assess the treatment effect of the CCL opening in the next section.

In Fig. 4, we plot log-housing price changes (estimated using the LPR) with respect to the sale time, which is indicated by the number of months starting from the first sample date of March 2007 in the window. The solid vertical line indicates the dates of the three phases of CCL MRT stations openings. The dashed non-linear line shows the price gradient for houses in the control group, and the prices are significantly higher than the price gradient of the treatment houses as represented by the darkened curved line in the first 20 months of the window prior to the opening of the CCL. The two price gradients converged at approximately 6 months before the opening of Phase 1 of the CCL. The capitalization effects in the post-CCL opening have been almost absorbed into houses in the treatment area 6 months prior to the Phase 1 opening of CCL (20th month); and thereafter, the prices in the treatment area and the control area are closely correlated. The early reaction to the CCL opening reveals strong "anticipative" effects from the housing markets, which were also found in McDonald and McMillen's (2004) study of Chicago's UTS line. We will conduct further tests on the "anticipative" effects in the following empirical sections.

4.3.2. Treatment zone

Based on the LPR model, we identify the cut-off of 600 m (by the network distance) to the nearest CCL MRT stations, at which we sort the samples into a treatment group (≤ 600 m) and a control group (> 600 m). We compute the descriptive statistics for the treatment zone (by the network distance) in Columns 4 and 5 of Table 2, and compare the statistics with a treatment zone defined by the Euclidean distance of 600 m (Columns 8 and 9). The compositions of the treatment samples based on the two different distance measures, network distance versus Euclidean distance, are different in various aspects. The sample size increases by more than double from 7388 to 15,429, when we change the cut-off measure from the network distance to the Euclidean distance, though the same cut-off of 600 m is kept. The average prices of the network-based treatment samples increase from S$1,192,170 (S $11,693 psm) to S$1,358,329 (S$12,349 psm) for the Euclidean-based samples. By the property type, the distributions between condominium and apartments are not significantly different between the two treatment samples; but EC are not found in the network-based treatment zone, whereas 0.9% of the samples in the Euclidean-based treatment zone are made up of EC. By land tenure, we also find relatively lower proportion of freehold properties relative to the leasehold properties (34.9%:65.1%) in the network-based treatment zone compared to the Euclidean-based treatment zone (47.7%:52.3%). In terms of buyer type (buyers currently living in public housing and those currently living in private housing) and sale types (new sale, resale and sub-sale), the variations between the two types of treatment zones are marginal.

When we compare the network-based treatment samples with the control samples that fall outside the 600 m network distance boundary (Columns 6 and 7), we find that our control samples are nearly two times the size of the treatment sample (14,566). However, the control samples are also characteristically very different from the treatment samples defined earlier. The average housing price in the control zone is much higher at S$1,512,530 (S$12,509 psm), which is approximately 26.8% higher than the average housing price in the treatment zone (network distance). Variations in the transaction characteristics are marginal, in term of property type, buyer type and sale type, except that most of the EC samples are found in the control zone. Houses in the control zone are larger by unit size (with average log-area of 4.674), but lower by height (average at 7.215 floors). There are more freeholdtenured houses in the control zone (59.5%) than in the treatment zone. We could not rule out that urban planners may "select" more densely built areas with lower surrounding land prices for new MRT stations.

Like in Linden and Rockoff's (2008) study, it is difficult to isolate the effects of housing location selection by sex offenders because sex offenders are more likely to sort into low income neighborhoods. In our context, urban planners with the land value recapture objective in mind are also more likely to locate MRT stations in high-density neighborhoods, or neighborhoods with elastic supply of land for new housing developments. The siting of the MRT station has more direct impact on housing values than the preference of living near an MRT station. However, due to difficulty in identifying buyers' and sellers' preferences, we are not able to explicitly correlate the capitalization effects of a purely random opening of a new MRT station event to the willingness to pay to live near an MRT station.

For the inter-temporal variations, we use the new CCL opening as a random and an exogenous shock to assess the pre-existing and the post-opening of new CCL stations on non-landed private housing values in a diff-in-diff model, which will be discussed in greater detail in the subsequent sections.

4.4. Spatial difference-in-differences (SDID) model specifications

The study sets up a quasi-experiment to test if both cross-sectional and temporal variations in housing prices were observed between neighborhoods with direct access to the new MRT stations and those that do not enjoy the new MRT effects. The two neighborhoods are identified by a binary variable, "Treat", which has a value of either 1 or 0 depending on whether a neighborhood receives the direct treatment benefits of the new CCL MRT stations. We apply the two spatial innovations, which include the network distance measure and the local polynomial regression, in defining the "Treat" variable to capture the physical proximity to the new MRT stations. The local polynomial regression graph (Fig. 3) shows a clear discontinuity in housing prices at the network distance of 600 m; and we use this distance as the reference cut-off to demarcate the treatment boundary of the impact zone of new CCL stations. For a robustness test, we experiment with a cut-off using 600 m Euclidean distance.

Simulating a random shock with the opening of the new CCL MRT stations, we include the "Post" dummy, which is defined as the opening of the CCL MRT stations, $[t \geq 0]$, to separate the pre-existing differences from the post-treatment differences in the housing prices between the two locations. Some may argue that differences in housing prices could be driven by omitted and cofounding variables that are uncorrelated with the MRT stations. For example, local improvement programs in neighborhoods may cause pre-existing changes in housing prices prior to the CCL MRT opening. We use an interaction term, "Treat × Post", which, if significant, should only be caused by the treatment effects specific to houses that are close to the new MRT stations. The housing price trend in the treatment neighborhood in the post-CCL opening periods should be different from the housing price trend in the control neighborhood.

The diff-in-diff model for the log-housing price, which controls for both spatial (distance to new CCL stations) and temporal variations (before and after the opening of new CCL stations), is specified as follows:

$$LnP = \alpha+\beta_1\times Post+\beta_2 \times Treat + \beta_3\times(Treat\times Post)+H'\gamma+N'\theta+\varphi+\tau+\epsilon \qquad (1)$$

where LnP is the housing price in the log-term; H is a vector of housing characteristics, such as floor area, floor height, type, lease tenure type, and sale type; N is a vector of locational amenities, such as distances to CBD, top primary schools, bus stops, expressways, and major shopping malls; φ is the spatial fixed effects included to control for unobserved spatial features within the postal sector, represented by the first two digits of the postal code; and τ is the time fixed effects that accounts for the quarter and the year temporal dynamics in the housing market. β_1, β_2, β_3, γ and θ are estimated coefficient vectors, and ε is an *i.i.d.* error term. We expect the coefficients β_3 to be significant and have a positive sign, if households capitalize the MRT accessibility benefits into housing prices after the new CCL MRT stations opening.

In the diff-in-diff approach, it is common for researchers to cluster unobserved variations within a small localized area using the spatial fixed effects. However, the recent literature has been increasingly concerned with non-stationarity caused by spatial interactions in the two adjacent neighborhoods, one in the treatment and another in the control areas. Anselin (1988) and Anselin and Arribas-Bel (2013) argue that failure to control for spatial dependence produces inefficient and biased estimates.

Spatial dependence could exist in the dependent variable and/or the error term; the former indicates a possible spatial spillover or diffusion process – an event in a place predicts an increased likelihood of a correlated event occurring in a neighboring place; and the latter is caused by omitted covariates that are spatially correlated. In our study, we expect the neighborhoods with the new MRT line to create spillover effects, either positively or negatively, onto the adjacent control neighborhoods. The reduction in car travel time (Baum-Snow and Kahn, 2000) induces car-owning house owners with relatively lower MWTP for living near MRT stations to move out of the treatment zone ("push factor") (Dubé, et al., 2014). Likewise, households with relatively high MWTP for MRT convenience may move out of the neighborhoods not served by the CCL MRT stations into the neighborhoods near the CCL MRT stations (treatment) ("pull factor").

In Singapore's context, the land value recapture strategy is used by the government through selling state lands near the MRT stations to private developers for housing and other development purposes; and the capital raised is usually channelled into a consolidated account that could be used to fund infrastructure projects, including the construction of new MRT lines. Increases in land supply induced by the government's land sales could be one source of spatially correlated errors that drives housing value near the MRT stations. The disproportionate increases in new housing supply in the area surrounding the MRT stations could create spatial non-stationarity, which, if not controlled for, could bias the estimation of the capitalization effects.

We introduce the third spatial innovation by incorporating a spatial lag term (SAC) (used to account for the spatially dependent responses) and a spatial error term (SARAR) (used to spatially dependent error) (Anselin, 1988) into the diff-in-diff model as in Eq. (1). The spatial diff-in-diff (SDID) model with the SAC/SARAR structure could be represented as follows:

$$LnP = \rho WLnP+X'\eta+uu = \lambda Wu+\epsilon \qquad (2)$$

where W is a spatially weighted matrix that captures spatial relations among the observations. In this study, W is a row-standardized matrix that assigns proportional weights to each neighbor in the 'neighborhood set' of each observation. We adopt a distance-band-based approach to decide the neighborhood of each observation, which assumes that there is no direct spatial influence between observations beyond a threshold distance (or bandwidth), thus properties within this distance are considered neighbors of a particular observation. We set the threshold distance at 1500 m.[11] X represents all the explanatory variables in Eq. (1); η is a coefficient vector of X*;* ε is an *i.i.d.* error term; ρ and λ capture the spatial dependence effects in the dependent variable and the error term, respectively. For the SAC/SARAR model, we simultaneously and jointly incorporate a spatial lag and a spatial error in the model. If $\rho = 0$, it reduces to a spatial error model

[11] We test different spatial weight matrix (by changing the threshold distance) for the SAC/SARAR model. All the major results still hold and the model using spatial weight matrix with 1500-m threshold distance has the best model fit. Therefore, we report the estimation results of models with 1500m threshold distance in Table 7.

Table 3
Results of Diff-in-Diff models.

	1	2	3	4	5
Treatment measure	Network distance ≤600 m				Linear Distance ≤ 600 m
Study boundary	1.6 km	1.6 km	1.6 km	2.0 km	1.6 km
Within 600 m of CCL station	−0.115*** (0.005)	−0.081*** (0.005)	0.025*** (0.004)	0.032*** (0.004)	0.006 (0.004)
Within 600 m of CCL station × Post Operation	0.129*** (0.008)	0.130*** (0.007)	0.106*** (0.005)	0.091*** (0.005)	0.079*** (0.006)
Post operation	−0.077*** (0.005)	−0.032*** (0.004)	−0.037*** (0.005)	−0.021*** (0.005)	−0.051*** (0.006)
Constant	9.730*** (0.019)	10.170*** (0.020)	10.270*** (0.022)	10.220*** (0.020)	10.200*** (0.025)
Structural characteristics	No	Yes	Yes	Yes	Yes
Neighborhood characteristics	No	Yes	Yes	Yes	Yes
Postal sector fixed effect	No	No	Yes	Yes	Yes
Transaction quarter fixed effect	No	No	Yes	Yes	Yes
Observations	21,954	21,954	21,954	25,102	21,954
R-squared	0.7705	0.8245	0.9160	0.9122	0.9129
Adjusted R-squared	0.7704	0.8244	0.9158	0.9119	0.9126

Notes: The table reports the results for the regressions with log-transaction price as the dependent variable. Models 1 to 3 and Model 5 are estimated using the sample of non-landed private housing units within 1600 m network distance from the closest CCL stations, and Model 4 uses a large study boundary demarcated by the network distance of 2000 m. In the models, the treatment variable is defined by the 600 m network distance from the CCL stations; "Post operation" is a time dummy that has a value of 1, if a transaction occurs after the CCL in operation; and 0 otherwise. The interactive variable: "Within 600 m of CCL station × Post operation" capture the treatment effect of the CCL on property values. We include other covariates such as housing attributes (log of floor area, floor level, and dummies on property type), lease type, purchaser type, and sale type. Neighborhood characteristics include distance to CBD, distance to the nearest top primary school, distance to shopping mall, distance to bus stop and distance to the expressway. The quarter of the year and postal sector fixed effects are included in the model, where the data consist of 24 quarters and 26 postal sectors. Standard errors are in parentheses.
*p < 0.01.
**p < 0.05.
*** p < 0.0001.

(SARAR); and likewise, if $\lambda = 0$, it reduces to a spatial lag model (SAC).

5. Empirical results

5.1. Impact of new MRT stations on housing prices

We estimate the baseline diff-in-diff model to empirically test the impact of the new CCL MRT line opening on the non-land private housing values. Our estimated results are reported in Table 3. Columns 1 to 4 are models that use the 600 m network distance as the cut-off to divide the sample area into a treatment zone and a control zone. Model 1 is the simplest baseline model with only the three variables: "*Treat*", "*Post*", and the interaction term "*Treat* × *Post*", and a constant term. Model 2 controls for housing-specific attributes (such as unit area, floor, property type, lease type), purchaser type, and sale type, and location-related amenities (such as distance to CBD, distance to top primary school, distance to bus stop, distance to expressway, and distance to major shopping malls). We cluster unobserved spatial and temporal dynamics in the housing prices by adding spatial fixed effects (using the 26 postal sectors), and time fixed effects (using the 24 quarters in the transaction date) to Model 3. For Models 1 to 3, the study area is bounded by the 1600 m buffer ring; and for Model 4, the study area is expanded by increasing the buffer ring to 2000 m.

In Models 1 and 2, the coefficient on "Treat" is significant, but negative, where we do not control for both observed and unobserved variations in housing attributes and spatial heterogeneity, and the fixed transaction (quarter) time effects. The negative "Treat" coefficient seems to be inconsistent with the predictive outcome indicating a price discount for non-landed private properties that are located within 600 m from the nearest CCL station by a network distance compared to houses in the control zone. The other two coefficients on "Post" and "Treat × Post" have the expected sign, and are significant. The negative "Post" coefficient indicates that there was a general declining trend in housing price after the opening of CCL and the positive interactive term "Treat x Post" shows positive capitalization effects (between 12.9% and 13.0%) for the treatment area relative to the control area reverting the general downward trend in the post-opening periods.

Column 3 show the results of a more robustly controlled Model 3, where the postal sector and transaction quarter fixed effects are included; and the model's R^2 increases significantly to 0.916 from 0.771 and 0.824 in Models 1 and 2, respectively. The results show consistent signs for the three variables of interest: the "Treat" coefficient indicates a price premium of 2.5%, on average, for houses located within 600 m (network distance) from the CCL MRT stations relative to other houses located outside the CCL zone; the "Post" coefficient indicates the same declining trend in non-landed housing prices in the study area after the opening of CCL; the diff-in-diff ("*Treat* × *Post*") coefficient is highly significant at less than 1%, and indicates significant capitalization effects of 10.6% for non-landed houses located in the treatment zone relative to other control sample houses after the opening of the CCL stations. The results imply that the new CCL opening increases buyers' MWTP for houses enjoying close proximity (600 m network distance) to CCL MRT stations.

We conduct a robustness check by expanding the outer buffer ring of the study area from 1600 m to 2000 m from the closest CCL stations; and the expanded study area also increases the housing samples from 21,954 to 25,102. The estimation results are shown in Column 4 of Table 3. By expanding the study area, we find a weaker treatment effect of 9.1% compared to 10.6% found in Model 3 using sample houses in a smaller area (≤ 1600 m radius). For comparison purposes, we also estimate a model that uses the 600 m Euclidean distance in lieu of the network distance in identifying the treatment zone, and report the results in Column 5 of Table 3. Keeping with the same study boundary (≤ 1600 m), the Euclidean distance of 600 m, however, increases the treatment sample houses from 7388 (Model 3) to 15,429 (Model 5); and we find that the interactive term is still significant, but the treatment effect reduces by 2.7% to 7.9% compared to the early network distance model (Column 3). The results imply that the use of Euclidean distance that ignores spatial and topographical constraints in the study area could lead to under-estimation of the capitalization effects.

5.2. Spatial variations in treatment effects

To explore the spatial diffusion effect, we divide the treatment zone into 3 sub-zones that are within 200 m, 200–400 m, and 400–600 m network distance to MRT stations, respectively. In Column 1 of Table 4, we explore spatial variations in prices within the treatment group by using only 7388 sample houses within the network distance of 600 m. The results show that the pre-opening housing price trends in the three sub-zones are significantly different. On average, the prices of houses in the inner rings of 200 m and 200–400 m of the CCL MRT stations are 4.9% and 3.2% lower than those located in the outer ring of 400–600 m of the CCL MRT stations. The treatment effects as shown by the housing prices in the two inner rings are 11.6% (0–200 m) and 7.6%

Table 4
Robustness tests: spatial diffusion effects.

Study boundary	1 0.6 km	2 1.6 km	3 1.6 km	4 1.6 km
Treat(0–200 m)	−0.049***		−0.009	−0.011
	(0.012)		(0.014)	(0.014)
Treat(200–400 m)	−0.032***		0.034***	0.033***
	(0.006)		(0.006)	(0.007)
Treat(400–600 m)			0.022***	0.020***
			(0.004)	(0.005)
Treat(0–600 m)		0.025***		
		(0.005)		
Treat(600–1000 m)		0.000		−0.004
		(0.005)		(0.005)
Interactive variable:				
Treat(0–200 m) × Post operation	0.116***		0.192***	0.196***
	(0.013)		(0.015)	(0.015)
Treat(200–400 m) × Post operation	0.076***		0.127***	0.131***
	(0.008)		(0.007)	(0.008)
Treat(400–600 m) × Post operation			0.054***	0.058***
			(0.007)	(0.007)
Treat(0–600 m)× Post operation		0.111***		
		(0.006)		
Treat(600 −1000m) × Post operation		0.009		0.008
		(0.006)		(0.006)
Post operation	−0.059***	−0.042***	−0.033***	−0.037***
	(0.007)	(0.006)	(0.005)	(0.006)
Constant	9.878***	10.260***	10.260***	10.260***
	(0.068)	(0.023)	(0.022)	(0.023)
Structural characteristics	Yes	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes	Yes
Postal sector fixed effect	Yes	Yes	Yes	Yes
Transaction quarter fixed effect	Yes	Yes	Yes	Yes
Observations	7,388	21,954	21,954	21,954
R-squared	0.9190	0.9160	0.9170	0.9170
Adjusted R-squared	0.9184	0.9158	0.9167	0.9167

Notes: The table reports the results for the regressions with log-transaction price as the dependent variable. The models are estimated using the sample of non-landed private housing units within 1600 m network distance from the closest CCL stations. In the models, the treatment variable is defined by different network distances from the CCL stations, "Treat(k)", where [k = (0–200 m, 200–400 m, 400–600 m, 0–600 m and 600–1000 m)]; "Post operation" is a time dummy that has a value of 1, if a transaction occurs after the CCL in operation; and 0 otherwise. The interactive variables: "Treat(k) × Post operation" capture the treatment effect of the CCL on property values. We include other covariates such as housing attributes (log of floor area, floor level, and dummies on property type), lease type, purchaser type, and sale type. Neighborhood characteristics include distance to CBD, distance to the nearest top primary school, distance to shopping mall, distance to bus stop and distance to the expressway. The quarter of the year and postal sector fixed effects are included in the model, where the data consist of 24 quarters and 26 postal sectors. Standard errors are in parentheses.
*p < 0.01.
**p < 0.05.
*** p < 0.0001.

(200–400 m) higher than those in the outer ring of the treatment zone (400–600 m) in the post-CCL opening period. The results are consistent with the graphical evidence estimated using LPR as in Fig. 3, which affirm that the pre-existing and the post-CCL opening price gradients are non-linear within the treatment area that is 600 m (by network distance) from the closest CCL MRT stations.

In Column 2, we expand the baseline model (as in Column 3 of Table 3) by adding an additional distance dummy comprising transactions located in the region between 600 m and 1000 m (network distance) from the CCL stations, and an interaction of the new distance dummy with the post-CCL station opening dummy, to the diff-in-diff model. The results are consistent with the early findings confirming that houses within the 600 m treatment zone in the post-CCL opening show significant price increases of 11.1% relative to houses in the control zone. We, however, do not find significant variations in housing prices between the area from 600 m to 1000 m and the rest of the control zone (1000 m to 1600 m). The results imply that the cut-off network distance estimated by the LPR is robust, which cleanly captures the treatment effects in the study area that is bounded by the 1600 m radius from the MRT stations.

In Columns 3 and 4 of Table 4, we added the inner treatment ring dummies representing areas within 200 m and 200–400 m network distances from the CCL stations to the baseline model (Column 3 of Table 3) and the extended model as in Column 2 of Table 4, respectively. The results again show significant variations in the treatment zone. The two inner rings show stronger housing price increases of between 19.2% and 19.6% (within 200 m of the CCL zone), and between 12.7% and 13.1% (200–400 m of the CCL zone), compared to 5.4% and 5.8% increases in housing prices in the outer treatment zone (400–600 m of the CCL zone). However, housing prices in the area just outside the treatment zone (600–1000 m from the CCL stations) are insignificantly different from other area in the outer ring of the control zone (1000–1600 m). The results again show significant variations in housing price trends within CCL impact zone, which could be ignored by a discrete treatment dummy variable.

5.3. Temporal variations in treatment effects

Unlike the information on the arrival of a convicted sexual offender into a neighborhood, which is rather discreet (Linden and Rockoff, 2008), an MRT project usually takes years to construct, and the progress during the construction period is usually visible to potential buyers and households in the neighborhood. The date of completion is also made known to the public via the local media. Therefore, in our tests, it is hard to fully eliminate any prior reactions in housing markets in anticipating the opening of the new CCL line. Based on Fig. 4, we could clearly see the divergence in prices between the treated and the untreated neighborhoods occurring way before the opening of the CCL, based on the event dates.

Unlike in the baseline diff-in-diff model, where the "*event date*" is used to create exogenous shocks, we use "calendar date" dummy in our tests for temporal treatment effects. When we test for the "anticipation" effects, we set the date of the first phase opening of CCL lines as [t=0], "$Post_{t=0}$", and use the two pre-CCL opening "calendar date" dummies to represent 6 months, "$Post_{t-6}$", and 12 months, "$Post_{t-12}$", respectively, before the opening of the first phase of the CCL lines. This setup could mitigate possible correlated effects of the sequential opening of CCL events; and the results are summarized in Table 5.

The results show that the treatment effects that are brought forward are significant and positive at 16.6% for the 1-year pre-opening period, "$Post_{t-12}$", and 13.6% for the 6-month pre-CCL opening period, "$Post_{t-6}$". The results affirm the graphical evidence on the "anticipation" effects as shown in Fig. 4. When we add the CCL opening event dummy, "$Post_{t=0}$", along with the 6-month pre-opening dummy, "$Post_{t-6}$", in Model 3, we find that though housing price premiums in the treatment zone are significant and positive relative to the control zone in both the 6-month pre-opening and the post-opening periods, the "anticipation" effects of the CCL opening diminish from 9.0% to 4.8%, when houses are sold nearer to the opening of the CCL stations.

As the CCL line opened in three stages, we test the inter-temporal variations between different phases by using the "calendar date" dummies (Phase 1: 28 May 2009; Phase 2: 17 April 2010; Phase 3: 8 October 2011) in the diff-in-diff models, and use only samples that are close to the CCL stations open in different phases in our estimation (See Appendix A). The results in Table 6 show that in Phase 1 of the

Table 5
Tests of "Anticipation" effects of the CCL opening.

Sample period	1 2007–2013	2 2007–2013	3 2007–2013
Within 600 m of CCL station	−0.064***	−0.033***	−0.034***
	(0.006)	(0.006)	(0.006)
$Post_{t-12}$	−0.061**		
	(0.020)		
$Post_{t-6}$		−0.225***	−0.211***
		(0.026)	(0.026)
$Post_{t=0}$			0.011
			(0.011)
Within 600 m of CCL station × $Post_{t-12}$	0.166***		
	(0.006)		
Within 600 m of CCL station × $Post_{t-6}$		0.136***	0.090***
		(0.006)	(0.015)
Within 600 m of CCL station × $Post_{t=0}$			0.048**
			(0.015)
Constant	10.310***	10.290***	10.290***
	(0.022)	(0.022)	(0.022)
Structural characteristics	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes
Postal sector fixed effect	Yes	Yes	Yes
Transaction quarter fixed effect	Yes	Yes	Yes
Observations	21,954	21,954	21,954
R-squared	0.9168	0.9165	0.9166
Adjusted R-squared	0.9166	0.9163	0.9163

Notes: The table reports the results for the regressions with log-transaction price as the dependent variable. The Models are estimated using the sample of non-landed private housing units within 1600 m network distance from the closest CCL stations. In the models, the treatment variable is defined by the 600 m network distance from the CCL stations; "$Post_{t=0}$" is a time dummy that indicate the opening of Phase 1 of the CCL in May 2009. For the tests of "anticipation" effects, we include two other time dummies: "$Post_{t-12}$" and "$Post_{t-6}$", which represent the 12 months and 6 months pre-CCL Phase 1 opening event dates, respectively. The interactive variable: "Within 600 m of CCL station × $Post_{t-k}$", where k=(0, 6, 12), capture the treatment effect of the CCL on property values. We include other covariates such as housing attributes (log of floor area, floor level, and dummies on property type), lease type, purchaser type, and sale type. Neighborhood characteristics include distance to CBD, distance to the nearest top primary school, distance to shopping mall, distance to bus stop and distance to the expressway. The quarter of the year and postal sector fixed effects are included in the model, where the data consist of 24 quarters and 26 postal sectors. Standard errors are in parentheses.
*$p < 0.01$.
** $p < 0.05$.
*** $p < 0.0001$.

Table 6
Tests of "Calendar Date" effects with different phases of opening of CCL.

	1	2	3
Treatment measure	Network Distance ≤ 600 m		
Study boundary	1.6 km	1.6 km	1.6 km
CCL Operation Phase	Phase 1	Phase 2	Phase 3
Within 600 m of CCL station	0.022**	0.031***	−0.025***
	(0.008)	(0.007)	(0.005)
Within 600 m of CCL station × Post Operation	0.002	0.040***	0.095***
	(0.008)	(0.008)	(0.009)
Post operation	0.088***	−0.014	−0.001
	(0.016)	(0.018)	(0.043)
Constant	10.360***	9.356***	10.310***
	(0.072)	(0.037)	(0.036)
Structural characteristics	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes
Postal sector fixed effect	Yes	Yes	Yes
Transaction quarter fixed effect	Yes	Yes	Yes
Observations	4,975	7,900	9,079
R-squared	0.9177	0.9270	0.9203
Adjusted R-squared	0.9170	0.9266	0.9199

Notes: The table reports the results for the regressions with log-transaction price as the dependent variable. The models are estimated using the sample of non-landed private housing units within 1600 m network distance from the closest CCL stations. In the models, the treatment variable is defined by the 600 m network distance from the CCL stations; "Post operation" is a time dummy that has a value of 1, if a transaction occurs after the CCL in operation; and 0 otherwise. The interactive variable: "Within 600 m of CCL station × Post operation" capture the treatment effect of the CCL on property values. We separately test the events using the opening of the 3 different phases of CCL in the tests (Phase 1: 28 May 2009; Phase 2: 17 April 2010; Phase 3: 8 October 2011). We include other covariates such as housing attributes (log of floor area, floor level, and dummies on property type), lease type, purchaser type, and sale type. Neighborhood characteristics include distance to CBD, distance to the nearest top primary school, distance to shopping mall, distance to bus stop and distance to the expressway. The quarter of the year and postal sector fixed effects are included in the model, where the data consist of 24 quarters and 26 postal sectors. Standard errors are in parentheses.
*$p < 0.01$.
** $p < 0.05$.
*** $p < 0.0001$.

CCL with the opening of only 5 stations on the lines, the treatment effects are positive, but statistically insignificant; and the subsequent opening of other stations in Phase 2 and Phase 3 show economically significant and positive treatment effects of 4.0% and 9.5%, respectively. The results seem to imply that most of the treatment effects found in the early models could be generated by the completion of Phase 2 and Phase 3 of the CCL line, which allows more seamless connectivity for commuters along the CCL to other MRT lines.

5.4. Spatial-dependence in price gradients

The OLS estimator assumes that the spatial structure remains static in the "pre-existing" and the "post-treatment" periods, and we cluster the errors at the postal sector level in the OLS-estimated diff-in-diff models discussed earlier. The static model reported in Column 1 of Table 7 (which is the same as the baseline Model 3 in Table 3) shows the treatment effect is 10.6%, which captures the price increases for houses with a network distance of less than 600 m from the closest MRT stations relative to houses located outside the 600 m accessibility range, in the post-CCL opening period.

In many recent spatial literature, the issues of spatial dynamics that allow for the inter-dependence of spatial structure between the treated zone and the untreated (control) zone, especially the spillover effects of the treatment to the contiguous control zones, could influence the causal inference. Like Heckert and Mennis (2012) and Dubé et al. (2011, 2013, 2014), we also account for spatial spillover effects in our model through the estimation of the spatial diff-in-diff (SDID) models. Columns 2 to 4 of Table 7 report the results of the three SDID models: SAC, SARAR and SAC/SARAR/ models. In the SAC-diff-in-diff and SARAR-diff-in-diff models, which incorporate the spatial lag of dependent variable and the spatial error term, respectively, the treatment effects are still statistically significant, but the magnitude of the post-CCL opening capitalization effects of the treated zone relative to the control zone changes to 10.8% and 9.7%, respectively. When both spatial dependence parameters are jointly modelled in the SAC/SARAR-diff-in-diff model (Column 4), the treatment effect reduces to 8.6% (Model 4). The results imply that spatial dependence is present in the form of both spatially clustered spillover effects across neighboring housing units and spatial interdependencies among unobserved attributes. If the spatial autocorrelation in housing price appreciations

Table 7
Spatial Dependence Diff-in-Diff (SDID) Models.

	0 OLS	1 SAC	2 SARAR	3 SAC/SARAR
Within 600 m of CCL station	0.025***	0.025***	0.039***	0.051***
	(0.004)	(0.004)	(0.004)	(0.004)
Within 600 m of CCL station * Post Operation	0.106***	0.108***	0.097***	0.086***
	(0.005)	(0.005)	(0.005)	(0.005)
Post operation	−0.037***	−0.043***	−0.026**	−0.024***
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	10.270***	2.936***	10.128***	1.667***
	(0.022)	(0.224)	(0.021)	(0.234)
Rho (spatial lag of dependent variable)		0.488***		0.573***
		(0.015)		(0.016)
Lambda (spatial error)			−2.178***	−2.178***
			(0.002)	(0.002)
Structural characteristics	Yes	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes	Yes
Postal sector fixed effect	Yes	Yes	Yes	Yes
Transaction quarter fixed effect	Yes	Yes	Yes	Yes
Observations	21,954	21,954	21,954	21,954
AIC	−18,045	−19,103	−19,891	−21,125

Notes: The table reports the results for the regressions with log-transaction price as the dependent variable. The models are estimated using the sample of non-landed private housing units within 1600 m network distance from the closest CCL stations. In the models, the treatment variable is defined by the 600 m network distance from the CCL stations; "Post operation" is a time dummy that has a value of 1, if a transaction occurs after the CCL in operation; and 0 otherwise. The interactive variable: "Within 600 m of CCL station × Post operation" capture the treatment effect of the CCL on property values. We include other covariates such as housing attributes (log of floor area, floor level, and dummies on property type), lease type, purchaser type, and sale type. Neighborhood characteristics include distance to CBD, distance to the nearest top primary school, distance to shopping mall, distance to bus stop, and distance to the expressway. The quarter of the year and postal sector fixed effects are included in the model, where the data consist of 24 quarters and 26 postal sectors. Model 1 is estimated using OLS estimator; Model 2 include a spatial lag variable (SAC); Model 3 include a spatial error term (SARAR), and Model 4 include both SAC and SARAR. Standard errors are in parentheses.

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

between the treated zone and the control zone are ignored, we may have had overestimated the capitalization effects by 2.0%. The results provide new evidence to support the spatial literature that argues for the need to address spatial non-stationarity in the models. Our results add new evidence to the early study by Dubé et al. (2011, 2013, 2014), which though finds no significant results when using the public mass transit system in Montreal, Canada, in the quasi-experiment.

5.5. Realized gains in housing values

Based on the static diff-in-diff Model in Column 1 of Table 7, we quantify the capitalization effect associated with the new CCL opening through accrued housing value increases in the treatment zone. For a non-landed private housing unit located within the impact zone of the CCL with an average transaction price of S$1,192,170, the CCL-associated treatment effects of 10.6% are translated into an average price premium of S$126,370. In aggregate terms, the realized gain in housing value associated with the new CCL is estimated to be approximately S$474.52 million based only on the aggregate value of S$4.42 billion estimated from the 3755 non-landed private housing transactions occurring in the impact zone after the opening of the new CCL. If the spatial dependence effects are accounted for, the realized gains in housing values from the CCL opening reduce, but still remain significant, to S$380.12 million.

The estimated capitalization effect is estimated to be approximately 7.1% of the estimated total construction cost of S$6.67 billion for the CCL line. This may be considered only as the lower bound as we only consider the 3755 transacted non-landed private housing after the post-CCL opening. It should be noted that the actual capitalization effects could be much larger, if the full housing stock along the CCL, the anticipative effects, and spillovers to the control zone are considered.

In the "Household Interview Travel Survey (HITS)" conducted by the LTA in 2012, the results show that over 77% of non-landed private housing owners living along the CCL own private cars. The car ownership ratio in the CCL treatment area is disproportionately higher than the average national car ownership rate of approximately 10 private cars per 100 people. Zhu and Diao (2016) find that the opening of CCL increases the density of upper- and upper-middle-class car-owning households in non-landed private houses along the CCL corridor. However, they also find that wealthy households living near the CCL reduce their car dependence by switching to MRT after the opening of the CCL. The non-pecuniary benefits associated with the opening of the CCL may come in the form of the reduction in marginal social costs for car users on the congested road. Baum-Snow and Kahn (2000) observe the same switching behaviour of private car users in the US.

6. Conclusion

OLS-based diff-in-diff models are a popular tool used in many quasi-experiment settings to establish causal-effects of new RTS lines on housing values. The diff-in-diff models exploit cross-sectional and inter-temporal variations in housing price trends before and after the opening of new RTS lines controlling for spatial and time fixed effects. However, the static diff-in-diff models ignore topographical features and spatial autocorrelation structure in local areas, which may lead to over-estimation of treatment effects of new transport infrastructure on housing values.

In a quasi-experiment involving the opening of the new CCL MRT line in Singapore, this study applies three advances in spatial econometrics to address the issues of spatial dynamics and spatial dependence structure. First, we use the network distance, instead of the Euclidean distance, to measure the accessibility of houses to the closest MRT stations taking into consideration existing road networks in the study area. Second, we adopt the local-polynomial-regression (LPR) approach as in Linden and Rockoff (2008) to estimate the housing price gradients before and after the new CCL station openings. We find that houses within 600 m network distance to the closest CCL stations experienced significant price appreciation relative to houses outside the 600 m zone. Based on the LPR-estimated cut-off network distance, we sort non-landed private housing samples into a treatment group and a control group to capture differential price dynamics in response to the new line opening events. Third, we estimate spatial diff-in-diff (SDID) models incorporated a spatial lag term (SAC), a spatial error term (SARAR) (used to spatially dependence errors), and both SAC/SARAR terms in the specification to assess the treatment effect of CCL.

Our results show that housing prices in the treatment zone increase by 10.6% relative to houses in the control zone after the opening of the CCL line using the static diff-in-diff models. The results are robust when we vary the study boundary from 1600 m to 2000 m. We also affirm that the treatment effects are non-linear with stronger treatment effects on houses located within the inner rings of the impact zone than houses in the outer ring (by network distance). We also find significant "anticipation" effects that appear as early as 12 months prior to the opening of the CCL line. When we use the "calendar dates" to separate the treatment effects for the three phases of CCL openings, we find significant positive treatment effects only in Phase 2 and Phase 3 of the CCL openings. The spatial autocorrelation and spillovers have important impact on the treatment – if not controlled for, these could lead to over-estimation of the treatment effects. In our SDID model with the incorporation of both the SAC and the SARAR terns, we find that the treatment effects are significant, but the magnitude reduces by 2.0% to 8.6%. This treatment effect is translated into realized gains of S$380.12 million in the private non-landed housing markets.

Our findings reinforce the results in the earlier literature showing significant housing price capitalization effects associated with public transport infrastructure investments. In our paper, we introduce new spatial innovations to explicitly control for spatial dynamics, in order to provide more reliable estimates of the capitalization effect of new urban RTS lines. The inter-dependence structure between the treatment zone and the control zone implies that new RTS lines may bring accessibility benefits to different neighborhoods. For example, in Singapore's context, if the new CCL line could induce more car owning upper- or upper-middle-income private households to switch to using MRT services, the new CCL could generate spatial spillovers in terms of reduced congestion on the roads in the control neighborhoods not served by the CCL line. Therefore, understanding the spatial dynamics associated with the new RTS infrastructure investments contributes to more informed policy design for value capture programs for urban planners, which may otherwise have had been neglected in the conventional cross-sectional analyses.

Appendix A. MRT stations on the circle line

No	Name of Station	MRT Station Code	Interchange Code	Connecting to
Phase 1 (Opening Date: 28 May 2009)				
1	Bartley	CC12		
2	Serangoon	CC13	NE12 / CC13	North-East Line
3	Lorong Chuan	CC14		
4	Bishan	CC15	NS17 / CC15	North-South Line
5	Marymount	CC16		
Phase 2 (Opening Date: 17 April 2010)				
6	Dhoby Ghaut	CC1	NS24 / NE6 / CC1	North-South/North-East Lines
7	Bras Basah	CC2		
8	Esplanade	CC3		
9	Nicoll Highway	CC5		
10	Stadium	CC6		
11	Mountbatten	CC7		
12	Dakota	CC8		
13	Paya Lebar	CC9	EW8 / CC9	East-West Line
14	Macpherson	CC10		
15	Tai Seng	CC11		
Phase 3 (Opening Date: 8 October 2011)				
16	Caldecott	CC17		
17	Bukit Brown#	CC18		
18	Botanic Gardens	CC19		
19	Farrer Road	CC20		
20	Holland Village	CC21		
21	Buona Vista	CC22	CC22/EW21	East-West Line
22	One North	CC23		
23	Kent Ridge	CC24		
24	Haw Par Villa	CC25		
25	Pasir Panjang	CC26		
26	Labrador	CC27		
27	Telok Blangah	CC28		
28	Harborfront	CC29	CC29/NE1	North-East line
Circle Line Extension (14 January 2012)				
29	Marina Bay	CC30	NS27 / CE2 / TS20	North-South Line /Terminal
30	Bayfront	CE1	CE1/DT16	Terminal / Downtown Line

Note: The stations in the Circle Line Extension opened on 14 January 2012 are not included in the study. # Bukit Brown station is also closed and reserved for future operation, and not included in our study. There are 3 more new stations being planned on the CCL (Keppel, Cantonment, and Prince Edward); and construction is scheduled to start in 2018, and the stations will open in 2025, which will complete the loop of CCL upon completion.

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