A Quantile Regression Analysis of Housing Price Distributions Near MRT Stations

Mi Diao[1], *Daniel P. McMillen*[2], *and Tien Foo Sing*[3]

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Abstract:

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 in Singapore. Using the network distance measure and a local-polynomial-regression approach, we observe discontinuity in housing prices at 600 meters radius from the closest CCL stations, and use it to divide the study area into the treatment zone and the control zone. Using the non-landed private property transaction data for the period from 2007 to 2013, we estimate the average treatment effects associated with the CCL opening at 8.96%. Using the quantile version of difference-in-differences (QDID) model, we also find significant distributional treatment effects in different price quantiles. The stronger effects are found in the 50th quantile houses at 9.26%, whereas the treatment effect are smaller in the 10th and 90th quantiles at 4.14% and 6.56%, respectively. When we adjust for spatial spillover in the model, the same distributional effects are still observed, but the magnitude of the quantile treatment effect is smaller. We next adopt the conditional quantile decomposition approach, and show that the price changes are attributed to both compositional changes and also the price elasticity changes. After the opening of CCL, transactions in the treatment area tend to be smaller, but more expensive; but the effects are weaker in the control area.

Keyword: *Average treatment effects, distributional quantile effects, spatial variations, quantile decomposition, spatial autocorrelation, price heterogeneity*

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1 *Department of Real Estate, National University of Singapore. Email: rstdm@nus.edu.sg*

2 *Department of Real Estate, University of Illinois at Chicago. Email: mcmillen@illinois.edu*

3 *Corresponding author. Institute of Real Estate Studies (IRES) / Department of Real Estate, National University of Singapore: Email: rststf@nus.edu.sg*

1. Introduction

The rail transit system (RTS), or more specifically known as the mass rapid transit (MRT) system in Singapore, has been an important infrastructure that has stimulated rapid urban renewal in the island-state since its introduction in 1987. Singapore's urban planners adopted the MRT system as the backbone of the city's transportation plan, and started building the rail infrastructure in 1980s. The MRT network enables decentralization of selected commercial activities to regional centres in the outskirt areas, and helps alleviates over-crowding and congestion in the central business district (CBD). With improved accessibility via the MRT system, households are also more willing to move to new housing estates located further away from the employment centres. As a result, the gap in land prices between the urban and the suburban areas becomes smaller flattening the bid rent gradient, a phenomenon that is also observed in many US cities.[1]

Starting with the two MRT lines (North-South and East-West) of approximately 100 kilometers (km) in 1987, the MRT network has been expanded progressively, and by 2030, the MRT network will double its current rail line to 360 km in length giving 8 out of 10 residents the convenience of walking to the nearest MRT stations within 10 minutes. Houses near MRT stations are well sought after by Singaporean households. An increasing marginal willingness-to-pay ("MWTP") to live in houses near to MRT stations has been supported by empirical evidence (Diao, Fan and Sing, 2017; Diao, Leonard and Sing, 2017). The capitalization of the proximity to RTS into housing prices have been one of the most widely studied topics in the urban economic literature (Edel and Sclar 1974; Hilber and Mayer, 2009; Diao, Leonard and Sing, 2017), and empirical evidence supporting such capitalization effects has also been found in many cities, and across different countries.[2]

[1] There is abundant of empirical evidence on the impact of the rail transit system on rent gradient in the US (Nelson, 1992; Gatzlaff and Smith, 1993; Landis et al., 1995; McDonald and Osuji, 1995; Bowes and Ihlanfeldt, 2001; McMillen and McDonald, 2004; and others).

[2] 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), Boston (Diao, 2015), 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) (Debrezione et al., 2011).

This study is an extension to an earlier study by Diao, Leonard and Sing (2017), which applies the spatial autoregressive difference-in-difference (SDID) model to empirically test the "MWTP" effects designed around the opening of the Circle MRT Line in Singapore. The earlier study uses the network-based distance measure coupled with the local polynomial regression to identify the treatment zone of MRT stations taking into account spatial and topographic features of the local road network. It then adds spatial autoregressive terms to the DID model to allow for local spillovers occurring around MRT stations. Despite allowing for the spatial-dependence in estimating MWTP, the DID model only estimates the average treatment effect (ATE), which assume constant differences effects on the outcomes for the treated group and the untreated (control) group over time. The ATE in our early study, or for this matters in other studies of ATE, does not examine distributional effects heterogeneity.

The objectives of the paper are two-fold. First, the paper is to extend the existing SDID to go beyond "the mean effects" by analyzing, if exist, the distributional treatment effects associated with the opening of MRT stations along the Circle Line in Singapore (or in short "CCL" opening). Adjusting for spatial autoregressive and covariates, we use the quantile version of the SDID model to examine the distributional treatment heterogeneity, which is also known as the quantile treatment effects (QTE). Second, it verifies if QTE is confounded with compositional changes in the housing samples after the CCL opening (treatment effects). We use the unconditional quantile decomposition methodology to separate changes associated with attributes (x variables) from those associated with the coefficients. The compositional changes in the sample could affect both the attributes and also the coefficients for different quantiles; but the spatial autoregressive structure could account for the coefficient changes, but not the structural compositions following the Circle Line treatment. However, if the CCL treatment cause where the structural components could be endogenous.

In this study, based on the same housing dataset as in the study by Diao, Leonard and Sing (2017), we estimate the spatial distribution of log-unit housing prices by distance to CCL stations before and after the opening of CCL using the locally weighted quantile regression with kernel weight, which follows McMillen's (2015) conditional parametric quantile model (CPAC) and is equivalent to the quantile version of the Linden and Rockoff's LPR model (2008) in identifying the impact zone of a treatment. We show significant variations in the distributional treatment effects when we separate the LPR estimates into 10%, 50% and 90% quantiles. Next, we estimate the QTE using the unconditional quantile spatial AR DID regression (or denoted as "QSDID").

This paper makes two significant extensions to Diao, Leonard and Sing (2017) that study the capitalization effects of the CCL opening. First, we use the same CCL opening in our quasi-experiment, and affirm the early finding of positive capitalization effects of the CCL opening. The ATE associated with the opening of CCL is estimated at about 8.96%. However, we find significant distributions in the treatment effects in the QDID model. The stronger effects are found in the 50^{th} quantile houses at 9.26%, whereas the treatment effects are smaller in the 10^{th} and 90^{th} quantiles at 4.14% and 6.56%, respectively. When we adjust for spatial spillover in the model, the same distributional effects are still observed, but the magnitude of QTE is smaller taking into account the spatial spillovers.

Second, we use the conditional quantile decomposition procedures proposed by Machado and Mata (2005), which is also used by McMillen (2008), to decompose the total price change after the CCL opening to the portion that are associated with attribute (variable) changes and price elasticity (coefficient) changes. We find that the CCL treatment causes compositional changes in the transactions where more large houses are displaced by small size houses, but the price elasticity for the houses in the treatment areas increases significantly. In short, the transactions in the CCL treatment area tend to have lower quality, but more expensive after the opening of the CCL; but the effects are weaker in the control area.

This paper is organized as follows. Section 2 gives a brief overview of the proposed quasi-experimental design that uses the Circle Line opening as the treatment. Section 3 describes the data and empirical methodology. Section 4 estimates the locally weighted quantile regression that shows distributions of the log-housing prices conditional on distance to the nearest MRT stations on the Circle Line. Section 4 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. The CCL Opening

The earliest MRT lines of 67-kilometre (km) criss-crossing the island from the North to the South and from the East to the West were built with an estimated budget of S$5.3 billion (in 1982 dollars) (US$4.18 billion). The two MRT lines were completed in approximately 5 years, and the MRT trains started running on the two lines in 1987. The North-South and East-West lines form the backbone of the MRT network of the island creating a new milestone for the public transportation system in Singapore.

In this study, we use the 4th MRT line in the island - the Circle Line ("CCL") with a total of 35.7 km in rail length and 30 stations (Appendix 1) for our experimental design. The CCL opened in three stages between 2009 and 2012:

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

In our design, we use the three different opening times associated with the opening of the MRT stations in the respective phases to define the exogenous shocks. We represent the temporal changes associated with each phase of the opening of the CCL by the time dummies, "$Post_i$". The time dummies, "$Post_i$" has a value of 1, if a sample transaction *i* occur on and after the opening date of its nearest CCL station; and otherwise 0. For example, a sample house *i* located near the closest Marymount Station has a value of 1 for the time dummy "$Post_i$" if the transaction occurs on or after 28 May 2009, and the value is 0, if the transaction occurs before 28 May 2009, otherwise. In this case, the calendar date of the opening of the respective phase of the CCL is used to identify the exogenous shocks in the experiment, rather than a single event date. In Diao, Leonard and Sing (2017), they also separately examine the three phases of CCL opening as independent events, but the results do not vary significantly from the joint estimates using the three different calendar dates in the analyses.

The CCL is a ring-shaped line connecting to the three existing lines via 6 interchanges (Figure 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. The CCL encircling the urban centre covers many of the most densely populated towns with a diverse mix of housing types (ranging from the mass market housing type to medium and luxury ranges of housing types). The diversity in the composition of housing type in the surrounding areas along the CCL lines is a perfect setting for us to examine the heterogeneity in the treatment to the CCL opening by examining the quantile distributional models. We also use the unconditional quantile decomposition regressions to further separate the covariate effects from the coefficient effects, and also to verify if the DID effects associated with the CCL opening were endogenously caused by compositional changes in the housing samples in both the treatment and the control areas.

3. Data Sources and Analysis

We use the non-landed private housing transactions for our empirical analyses, which consist of executive condominiums (EC), apartments and condominiums, where EC is subject to a 5 years occupation restriction before it could be sold in the market, and the latter two (apartment and condominiums) are have the full *laisser-faire* rights of transfer with no minimum occupation restrictions. Apartment and condominium samples constitute more than 99.4% of the sample in our analyses. Private landed houses that are more heterogeneous are not used in this study because of relatively thin transactions in the markets. Public resale market (excluding executive condominiums), which covers more than 70% of the housing stock in Singapore, is also not included in this study, because it is a more restricted housing market that excludes foreign buyers from the market.

The transaction data are obtained from the “REALIS” database, a real estate information system published by the Urban Redevelopment Authority (URA), covering a 6-year period from April 2007 to March 2013. To mitigate possible boundary discontinuity design problems (Black, 1981), we truncate our sample houses that are located outside 1.6 km radius from the closest CCL stations, and retain a final sample of 21,954 non-landed private housing transactions in our analyses. The sample housing transactions are represented by the green dots in Figure 1. As robustness tests, we expand the study areas to 2.0 km radius to the closest CCL stations.

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. In Singapore, each building is represented by a unique 6-digit postal code, and we could measure the distance of the unit (based on the 6-digit postal code) to the nearest MRT stations using the geographic information systems (GIS) tool. We also measure other spatial distances of each sample house to local amenities, including CBD, top primary schools, major shopping malls, bus stops, and expressways, and use them as control variables in the regressions. The summary statistics for the spatial variables are summarized in Table 1.

The first two columns of Table 1 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) [3], 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 height is 7.8 reflecting the high-density living 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 typical 99-year "Leasehold" lands. Based on his/her current address, a buyer type dummy ("private") divides the buyers into a public buyers, ("private" =0), if he/she live in a public flat, and otherwise, he/she is a private buyer whose current house is a private apartment ("private" =1); and the private buyers (67.7%) are the two times the number of public buyers (32.3%) in the sample. By housing type, the housing transactions are grouped into one of the 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%).

[Insert Table 1 here]

[3] The exchange rate is based on 1 US$ = 1.267S$ as on 31 December 2013 (Source: finance.Yahoo.com).

4. The Quasi-Experimental Design

4.1. Defining the Treatment Effects

In the early paper by Diao, Leonard and Sing (2017), they apply the network distance to measure the accessibility to the nearest MRT, which is a more practical and realistic distance measure, where geographical and physical obstacles are adjusted to minimize distortions to the Euclidean distance measures. They also use the local polynomial regression (LPR) like in Linden and Rockoff (2008) to identify differential (non-linear) treatment effects of the CCL opening on surrounding houses. We apply the same techniques, which include the network distance measure and the LPR[4], to define the treatment boundary in our experimental design.

The LPR estimates the mean unit price of the sample houses conditional on the distances to the closest CCL MRT stations before and after the openning; and the results show a significant price divergence in prices for houses that are located within 600 m network distance to CCL stations relative to other houses outside the 600 m range. Based on the cut-off of 600 m (network distance), we sort the samples into a treatment group (≤ 600 m) and a control group (> 600 m), and define a new variable "$Treat_i$" that has a value for 1, if a housing sample *i* is sorted into the treatment group; and otherwise 0 for the control group. We use the opening of the closest MRT stations of property *i* in the respective phase, "$Post_{i,}$", to determine the pre-treatment and post-treatment effects on house price changes.

The descriptive statistics for the two groups are separately represented in Table 1; and the control group samples (14,566) (Columns 3-6) are nearly two times the size of the treatment sample (7,388) (Columns 7-10). We also further sub-divide the sample periods into "Before" ("$Post_i = 0$) (Columns 3, 4, 7 and 8) and "After" ($Post_i = 1$) (Columns 5, 6, 9 and 10) the CCL opening, respectively for the treatment group and the control group sample in Table 1. The results show that in the pre-treatment periods (before the opening of CCL), the average price of S$1,720,472 (US$1,357,910) for the control group housing is about 28.2% higher than the average price of S$1,235,567

4 The technical details of the two methodologies are found in Diao, Leonard and Sing's paper that is forthcoming in the Regional Science and Urban Economics.

(US$975,191). However, in the post-treatment periods, the price gap between the two housing groups narrow to 8.72% with the average prices of S$1,146,814 (US$905,141) and S$1,256,449 (US$991,672) for the treatment and the control, respectively. In the housing attributes, we find that housing units sold in the control area (further away from the CCL MRT stations) are generally larger in size; whereas and transacted housing units in the treatment area (closer to the CCL MRT stations) (8.195 and 9.680) are higher in term of floor level.

In term of housing type, we see significant increases in smaller scaled developments in the form of apartment type, compared to the larger developments with full-scaled facilities found in condominiums after the opening of CCL. The drop is the most drastic in the control area from 71.3% to 53.8%, whereas a smaller drop from 61% to 59.7% is observed in the treatment area. It seems like the condominium demand has been "substituted" by lower price apartments, and the effect is more notably in the control areas that are further away from the CCL MRT stations. By land tenure type, we saw a sharp decline in "freehold" transactions from 44.5% to 25.5% in the treatment area, where freehold transactions also declined from 63.0% to 55.3% in the control area. The results could imply that most of the privately held freehold lands may have been acquired for the MRT stations construction, which is used by the government as a way to supplement public financing for such the MRT projects. The lands were subsequently sold to private developers on 99-year leases, which is shown by the marked increases in leasehold transactions from 55.5% to 74.5% in the area more affected by MRT construction (treatment area), compared to the increase from 37.0% to 44.7% in the control area. The heterogeneity in the attributes of housing transacted in the two areas seems to suggest possible compositional changes in housing sample "before" and "after" the CCL opening, which could potentially cause endogeneity bias, if unadjusted, to the estimates of the MWTP associated with the accessibility to the new CCL MRT line. We would apply quantile decomposition methodology to separate structure and coefficient changes for the two areas before and after the CCL opening.

In term of buyer type, more public housing upgraders (HDB buyers) entered the non-landed transaction markets after the CCL opening, where we observe 7.5% and 17.4% shift in the transaction activities from private to public buyers in the treatment area and the control area, respectively. More new housing sales were launched, which estimated at 57.1% and 55.2% in both the treatment area and the control area compared to the pre-opening new housing transactions of 49.6% and 45.7% in the two areas, respectively. We also include the spatial characteristics in the two areas in the pre- and the post-CCL opening periods, and the results again show heterogeneity in the spatial attributes in the housing samples.

4.2. Quantile Treatment Effects (QTE)

While the mean log-price is one of the most stable measures, it is susceptible to the influence of few large outliers. The median price measure could though overcome the outlier problem, but it is like the mean, both are a point estimate that could not capture the distributional effects in prices, especially if heterogeneity is found in MWTP of buyers in different sub-segment of the housing markets. In Table 2, we report alongside the mean log-price of houses, the distributional statistics in terms of the log-prices at the median, 10^{th}, 25^{th}, 75^{th} and 90^{th} percentiles, the differences before and after the treatment effects (the CCL opening) and also the difference in differences measures that capture the variations of the treatment effects over time before and after the CCL opening.

[Insert Table 2 here]

If we look only at the mean price differences in Columns (5) and (6), the housing transaction prices in both the treatment and the control areas decline after the CCL opening, and a larger decline is about 10 times more in the control area (-29.8%) relative to the treatment area (-2.7%). The positive (unconditional) mean difference-in-differences (DID) effects as indicated in Column 7 indicate that the CCL opening has positive impact on the housing prices in area that are close to the CCL MRT stations (treatment), and significantly narrow the gap in prices for houses in the treatment area relative to those more expensive houses in the control area. The median housing price DID shows the similar results, and indeed the magnitude of the CCL treatment effects is stronger at 31.8% relatively to the average (mean) treatment effect (ATE) of 27.1%.

However, when we look at the quantile treatment effects (QTE) across different housing segments, we find significant heterogeneity in the treatment effects across different housing quantiles, (τ = 0.10, 0.25, 0.75, 0.90). Like the median price, the prices in the 10^{th} and 25^{th} percentile treatment group increases after the CCL opening by 7.6% and 8.4%, respectively. The DID effects are also the strongest at 41.4% and 33.4% for the 10^{th} and 25th price quantiles, respectively. For the 75^{th} and 90^{th} housing price quantiles, prices in the treatment group decline 11.8% and 26.6%, respectively; and the DID effects are also weaker at 21.4% and 3.3%, respectively, implying that buyers of houses in the high price segment have relatively lower MWTP than buyers in the low-price housing segments.

Based on the cut-of boundary of 600 m, we add the quantile structure to the LPR model to account for distributional treatment effects for the control and the treatment samples. We estimate the quantile version of the LPR, and plot the 10% (dashed lines), 50% (darkened lines) and 90% (dotted lines) quantiles price distributions separately both before (blue lines) and after (red lines) the CCL openings against the distance to the closest MRT stations. In Figure 2, the darken lines that represent the median LPR prices show similar trends as the mean LPR price in Diao, Leonard and Sing (2017), where we find significant divergence in prices for houses that are less than 600 m from the MRT stations and no significant variations in log-prices for houses outside 600m radius from the MRT stations (the control zone). We also do not observe clear price variations in the 90^{th} price quantiles, where the two dotted lines both before (blue line) and after (red line) the CCL opening move close to each other across the range of network distance. For the 10^{th} percentile housing price trends (the dashed lines), we find a positive price gap between the post-CCL opening housing prices (red dashed line) and the pre-CCL opening housing prices across the full range of distance to the closest MRT stations. It seems like the price increases are not limited to only the treatment zone, but possibly spill over to the control zone. We would further examine the heterogeneity in the subsequent section using the quantile decomposition methodology.

4.3. *Quantile Spatial Autoregressive Difference-in-Differences (QSDID) Model*

Diao, Leonard and Sing (2017) uses the spatial autoregressive DID (SDID) model to estimate the ATE associated with the opening of CCL. In this paper, we extend the previous study to examine the heterogeneity in the treatment effects across different price quantiles (QTE). The basic quantile DID model can be written as follows:

$$Y_i = \alpha_i(\tau) + X_i\beta(\tau) + DID_i\Phi(\tau) + \psi_i(\tau) + \zeta_t(\tau) + \varepsilon_i(\tau) \quad (1)$$

The treatment effects are captured by the DID terms:

$$DID\Phi(\tau) = \delta_1(\tau) \times Post_i + \delta_2(\tau) \times Treat_i + \delta_3(\tau) \times (Treat_i \times Post_i) \quad (2)$$

Where α_i denote the intercept term, ψ_i denote the planning area dummy included in the model as the spatial fixed effects, ζ_t is quarter and the year of sale dummy that is included as the time fixed effects to account for time trends in the housing market, and ε_i denotes the standard *i.i.d.* error term. In the model, we use the log housing price, "$Y_i = LnP_i$", as the dependent variable, and X_i is a vector representing housing attributes, such as floor area, floor height, type, lease tenure type, and sale type, and also spatial amenities, such as distances to CBD, top primary schools, bus stops, expressways, and major shopping malls; τ is a particular quantile; β and Φ are coefficient matrices that measure the strength of the association of the vectors. $\delta_3(\tau)$ captures the QTE. We expect the coefficient $\delta_3(\tau)$ to be significant and have a positive sign, if the capitalization of the MRT accessibility benefits is positive after the new CCL MRT stations open.

We further extend the base QDID model to allow for the existence of spatial dependence by adopting the spatial AR quantile model described in McMillen (2015). The conditional quantile spatial autoregressive DID models (or "QSDID") model can be written as follows:

$$Y_i = \theta(\tau)WY_i + \alpha_i(\tau) + X_i\beta(\tau) + DID_i\Phi(\tau) + \psi_i(\tau) + \zeta_t(\tau) + \varepsilon_i(\tau) \tag{3}$$

$$DID\Phi(\tau) = \delta_1(\tau) \times Post_i + \delta_2(\tau) \times Treat_i + \delta_3(\tau) \times (Treat_i \times Post_i) \tag{4}$$

Where W is the row-standardized spatial weight matrix.

4.4. Conditional Quantile Decomposition

In the standard quasi-experiment using the DID approach, we assume the average treatment effects (ATE) in housing prices conditional on the distance to the MRT stations. However, in our QSDID model, the quantile treatment effects (QTE) allow heterogeneity in distributional treatment effects for different the two target point, which in our case include the two zone (the control zone and the treatment zone), and over two time period (before and after the CCL closing). We can no longer assume a constant shift in housing prices as a result of capitalization effects on the opening of the new CCL; and prices in the luxury segment of the housing market may respond differently to the exogenous shock than those in the low-price segment. If distributional treatment effect were solely caused by the capitalization effects of the proximity to MRT, the results will be straightforward to interpret. However, the presence of MRT could also bring other unintended impact to the surrounding housing attributes and amenities. While the spatial autoregressive term could account for the spillover effects in term of prices, the spatial adjustment, however, could not explain changes that are associated with structure attributes and spatial composition. For example, with the lands surrounding the new MRT stations significantly appreciate in values, older developments that are structurally sound, but not economically viable [5] become potential targets for redevelopment by private developers.

Developers who purchase lands surrounding the MRT stations at significantly higher prices are expected to intensify the lands use by redeveloping the lands for high-density and better-quality houses, and also sell them for higher prices in the market. The new developments are denser, with more but smaller size units; and more expensive in term of unit price. Therefore, it would be difficult to disentangle the new CCL treatment effects that are associated with the accessibility premiums, and those that are caused by change in housing composition and structural attributes in the treatment area vis-à-vis the control area. There are also other possible endogeneity issues that could also cause price increases for houses in the treatment area. We are not able to rule out value increases caused by owners of houses near the CCL MRT stations have higher propensity to carry out renovations and improvements to increase their house values (Harding, Rosenthal and Sirmans, 2007). With better connectivity to MRT, more commercial uses, such as retails and offices, which could afford to pay higher rents, could be attracted to the areas, and cause housing price increases that are uncorrelated with the MRT treatment effects, but improved local amenities in the treatment areas.

In our attempt to disentangle the treatment effects from other uncorrelated price effects, we propose to the use the quantile estimation methodology proposed by Machato and Mata (2005) to decompose the price changes in the treatment and control areas into the portion associated with the changing hedonic coefficients and the other portion associated with changing housing attributes (changes in the explanatory variables), respectively. In the linear decomposition methodology proposed by Oaxaca (1973), a Hedonic price model can be written into a reduced form as $Y = Z\rho + \varepsilon$, where Z denotes the matrix of explanatory variables; ρ denotes the coefficient vector, and ε

[55] In Singapore, strata-titled owners of many older residential developments have banded hands to sell their developments en bloc for prices that are doubled or more in some cases than what they could sell units individually in open market. The "windfall" is accumulated because the redevelopment values of the lands far outweighed the "marriage" value of the land and the old structure thereon.

denotes the error term. Using the subscript 0 and 1 to represent both the pre- and the post-CCL opening periods, the Oaxaca's decomposition could be written as follows:

$$E(Y_1 - Y_0) = (Z_1 - Z_0)\rho_1 + Z_0(\rho_1 - \rho_0) \tag{5}$$

Where $(Z_1 - Z_0)\rho_1$ represents changes in property attributes and $Z_0(\rho_1 - \rho_0)$ represents changes in the coefficients.

For the quantile version of decomposition approach, we follow the procedures proposed by Machato and Mata (2005), and the details are also available in McMillen (2008).

1) We estimate four sets of quantile regression models for the treatment and control areas before and after the opening of CCL, respectively. The dependent variable is the log of transaction price and the independent variables include housing attributes, spatial amenities, spatial fixed effects and time fixed effects. For each set of models, we estimate the coefficient vector for a set of 50 quantile values, (τ = 0.01, 0.03, … 0.99) with an incremental interval of 0.02. We use Z_{10}, Z_{11}, Z_{00}, and Z_{01} to represent the explanatory variables and use $\widehat{\rho_{10}}$, $\widehat{\rho_{11}}$, $\widehat{\rho_{00}}$, and $\widehat{\rho_{01}}$ to represent the vector of coefficients in the four sets of quantile models where the first subscript indicates either the treatment group ("1") or the control group (0), and the second subscript indicates either the post-CCL opening period ("1") or the pre-CCL opening period.

2) For the treatment group, we draw randomly with replacement 10,000 times from Z_{10}, Z_{11}, $\widehat{\rho_{10}}$, and $\widehat{\rho_{11}}$, respectively. We estimate the density functions $Z_{10}\widehat{\rho_{10}}$, $Z_{10}\widehat{\rho_{11}}$, and $Z_{11}\widehat{\rho_{11}}$ and use the functions to decompose the total change in the distribution of the predicted housing prices as follows:

$$(Z_{11}\widehat{\rho_{11}} - Z_{10}\widehat{\rho_{10}}) = (Z_{11}\widehat{\rho_{11}} - Z_{10}\widehat{\rho_{11}}) + (Z_{10}\widehat{\rho_{11}} - Z_{10}\widehat{\rho_{10}}) \tag{6}$$

Where the first term $(Z_{11}\widehat{\rho_{11}} - Z_{10}\widehat{\rho_{11}})$ captures the portion of distributional changes associated with explanatory variables, and the second term $(Z_{10}\widehat{\rho_{11}} - Z_{10}\widehat{\rho_{10}})$ captures the portion of distributions changes associated with the coefficients.

3) We repeat step 2 for the control group and decompose the total price change in the control group into attribute change and coefficient change as follows:

$$(Z_{01}\widehat{\rho_{01}} - Z_{00}\widehat{\rho_{00}}) = (Z_{01}\widehat{\rho_{01}} - Z_{00}\widehat{\rho_{01}}) + (Z_{00}\widehat{\rho_{01}} - Z_{00}\widehat{\rho_{00}}) \tag{7}$$

Where $(Z_{01}\widehat{\rho_{01}} - Z_{00}\widehat{\rho_{01}})$ represents attribute change and $(Z_{00}\widehat{\rho_{01}} - Z_{00}\widehat{\rho_{00}})$ represents coefficient change.

5. Empirical Results

5.1. *Impact of new MRT Stations on Housing Prices*

The first set of empirical results in Table 3 report the standard baseline ordinary least square (OLS) DID model (Column 1 of Table 3) to empirically test the impact of the new CCL MRT line opening on the non-land private housing values in Singapore. We then extend the ATE effects by allowing for distributional effects in the quantile version of the DID model (Columns 2 to 5 of Table 3), and lastly the quantile models are further extended by adding the spatial weight structure to account for possible spatial and temporal spillover treatment effects in different housing price quantiles (Table 4).

[Insert Table 3 here]

Column 1 of Table 3 shows the baseline OLS-DID result that simply tests the ATE associated with the CCL opening. The three key variables of interests are "*Treat*", "*Post*", and the interaction term "*Treat* × *Post*". The coefficient on "*Treat*" is significant, and positive indicating that housing prices in the areas that are within 600m (network distance) zone are, on average, 1.96% higher than the control group area outside the 600m zone from the CCL MRT stations. However, the coefficient on "Post" is also significant, but negative, which indicates general declining trend in housing prices, which see housing prices depreciate by 3.48% before and after the CCL operations. The negative price trends coincide with the government's introduction of a series of cooling measures that attempt to curb speculative activities between 2010-2013 (Diao, Fan and Sing, 2018). Most importantly, and consistent with the early results of Diao, Leonard and Sing (2017), the DID variables (the interaction between "Treat" and "Post"), we find evidence supporting significant and positive capitalization effects. The result indicates that process for non-landed houses located in the treatment zone increase by 8.95% relative to houses in the control zone after the CCL opening.

The results could not rule out the hypothesis that the new CCL opening increases buyers' MWTP for houses that are within 600m network zone to the CCL MRT stations.

The baseline OLS-DID model 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). The coefficients on all the control variables are significant, and have the consistent and right signs at less than 1% level.

We cluster unobserved spatial and temporal dynamics in the housing prices by adding spatial fixed effects (using the 12 planning areas), and time fixed effects (using the 24 quarters of the transaction date). To mitigate boundary discontinuity problem, we define a restrictive study area demarcated by a 1,600m buffer ring. However, when we expand the study area using a larger buffer ring of 2,000m, the results remain consistent and robust.[6] The same model structure with the housing and spatial covariates, and the planning area and the quarter and the year fixed effects are used in all other models in Tables 3 and 4.

5.2. Quantile Treatment Effects (QTE)

ATE overlook the heterogeneity of the treatment effect across price quantiles. We first provide graphic evidence on the heterogeneous price change before and after the CCL opening across different housing segments and then calibrate quantile regression models to estimate the QTE. In Figure 3, we plot the cumulative density function (CDF) of log unit price for the treatment group (left-hand panel) and the control group (right-hand panel), where the cumulative density for the pre- and post-CCL opening periods are represented by the red darkened line and the blue darkened line, respectively. For the treatment group, the Figure shows significance divergence in CDF between the period for the middle price range between 8.5 and 9.5 (in log-term), and the prices converge in the two tailed-end between the period. However, the price differences in the control group are less significant, we observe declines in the CDF for the mid-priced houses; but the

6 Due to space consideration, the robustness test results using the 2,000 m market area are not reported in the paper.

number of high end prices increase significant for the high-priced range. We derive the changes in CDF for both the treatment group (red darkened line) and the control group (blue dotted line), and plot the CDF changes against the price quantile in the x-axis in Figure 4. The results show more clearly a large gap in the CDF in the mid-priced quantiles (between 20th and 50th).

[Insert Figures 3 and 4 here]

For Columns 2 to 4 of Table 3, we present the standard quantile results (without adjusting for sptial spillover effects) for the three housing quantiles (10%, 50% and 90%) by the log-price. We find significant results on the DID terms at less than 1% level, and all the coefficients are with the same signs. The results indicate that highly heterogeneity in the treatment across the three housing quantiles, and the standard DID estimates may under-estimate the treatment effect in some housing quantiles, but over-estimate the effects in other housing quantiles. The "Treat" coefficients show that differences in prices are larger at 3.88% and 2.29% between the lower 10th and 50th quantiles of houses that located in proximity and those outside the MRT stations. The differential price effects are significantly smaller at only 0.49% for the luxury housing prices in the 90th quantile. The declining rates are also different between the low and mid-range price quantiles, which saw drops of 4.14% and 4.49% in the 10th and 50th price quantile; whereas housing prices in the 90th quantile are relatively more resilient, and decline by a smaller margin 2.63% after the CCL opening. Our results also show significant QTE, based on the interaction term, "Post × Treat", where the strongest treatment effect is found in houses in the 50th quantile, where price increases of 9.26%, which is above the ATE of 8.96%, which could be caused by the CCL opening. However, the effects of the CCL opening on the 10th and 90th quantiles are relatively smaller, though still significant, with the magnitude of 4.14% and 6.56%., respectively.

In Table 4, we add the spatial autoregressive controls into the QDID model, and the results again affirm the heterogeneity in the distributional treatment effects on the housing prices. However, the treatment effects are smaller, after we separately control for the dynamic spillovers of the price effects that could affect neighbouring houses over time. Again, the same distributional patterns in the treatment effects are observed, where the 50th quantile housing prices respond most strongly by 6.15%; followed by 5.89% and 3.24% in price increases in the 90th and 10th quantile housing prices.

We plot the distributional treatment effects estimated using QDID (blue dashed line) and QSDID (red dotted line) models, together with the 90% confidence ranges in Figure 5. Using the ATE effects as estimated by the standard DID model (black darkened line), the results show significant heterogeneity in the CCL opening treatment effects. The QTE estimated by the QDID shows that 50^{th} quantile housing prices is higher than the ATE, but the two tails of the treatment effects (10^{th} and 90^{th} quantiles) are smaller than the ATE. We also find that the spatial spillovers push the QTE (the red dotted line) below the ATE line and also the blue dashed line (unadjusted for spatial dynamics), and the results imply that if the dynamic spillovers are adjusted for, we may over-estimate the treatment effects (both ATE and QTE) in DID QDID models, respectively.

[Insert Figure 5 here]

The above results imply that the standard DID models could significantly over-estimate capitalization effects associated with the new RTS line, or more specifically the CCL opening in our context, if we neglect the spatial spillovers and also the heterogeneity in the treatment effects. We are likely to over-estimate the treatment effects for the low- and the high- price quantiles, but underestimate the mid-price quantile of houses. Adding values to the SDID models of Heckert and Mennis (2012), Dube, Legros, Theriault and Rosiers (2014)[7], and Diao, Leonard and Sing (2017), our results add new evidence supporting the heterogeneity in the distributional effects after controlling for the spatial autocorrelated structure of housing prices. The results imply that the CCL opening may bring about changes in both the housing structure and also the price elasticity for different housing submarkets that are associated with the CCL opening effects. We conduct further analysis using the conditional decomposition approach in the next section.

5.3. Decomposition of Treatment Effects

We follow Machado and Mata (2005)'s quantile decomposition approach, which was also used in McMillen (2008) to decompose the treatment effects into the portion attributed to the change in

[7] Dube, Legros, Theriault and Rosiers (2014) find no significant results when using the public mass transit system in Montreal, Canada, in the quasi-experiment.

attributes (the control variables) and the portion attributed to the coefficient changes, conditional of four target groups (as identified by the "Post × Treat" interaction term). We report the estimation results of the decomposition effects sorted into different quantiles, [τ = (0.1, 0.2, …. 0.90)], in Table 5. The results show the total differences, the two decomposed differences attributed to the variable effects and coefficient effects for the treatment group (left panel) and the control group. For the treatment group, the total differences are positive ranging from 0.118 to 0.152 for the 10th to 90th housing quantiles. The highest total difference of 0.22 is found in the 20th price quantile; and we also observe interesting results that show that the variable changes are negative in all the quantiles, and the coefficient effects are positive in all quantiles.

[Insert Table 5 here]

For the control group, the decomposition results are in contrast to those observed in the treatment group. The total differences are negative ranging from -0.201 to -0.281 for the 10th to 90th quantiles, and again the largest negative difference is found in the 90th quantile houses. While we find that the same negative structural variable effects and positive coefficient effects, but magnitude of the variable effects are larger, and the coefficient effects are smaller relative to those estimated in the treatment group in all price quantiles.

We also present the density functions of housing prices and the decomposition of density change in Figures 6 and 7. In figure 6, the density functions of $Z_{10}\widehat{\rho_{10}}$, $Z_{10}\widehat{\rho_{11}}$, and $Z_{11}\widehat{\rho_{11}}$ are represented by the green dotted line, the red dashed line and the solid blue line in the left panel (treatment group), respectively. The density functions of $Z_{00}\widehat{\rho_{00}}$, $Z_{00}\widehat{\rho_{01}}$, and $Z_{01}\widehat{\rho_{01}}$ are represented by the corresponding lines in the right panel (control group). Figure 6 shows significantly more narrow and skewed distributions of the density functions for the treatment group (left-hand panel), whereas the control group (right-hand panel) has the flatter distribution functions. The total differences changes are also more concentrated in the middle price quantile between 13.5 and 14.5 (in logarithm term). In Figure 7, we further decompose the density changes for the total difference (darkened blue line), and also derive the portion of differences attributed to structural characteristics changes (red dotted line) and the portion attributed to the coefficient (price elasticity) changes (green dashed line). We see much stronger density function changes in the treatment group (left panel) relative to the control group (right panel). For the control group, we observe negative total price changes in the low to mid-price ranges, and positive total price change in the high-price ranges. The total differences are driven mainly by increases in structural changes (smaller units) in the low to mid-price range housing segment, and decreases structural changes (reduction in larger units) in the high price-range houses. Whereas, the price elasticity effects decline in the lower price range, but the price elasticity is higher in the high price range. The results imply that in the treatment area, we expect significant but contrasting changes in both structural attributes and price elasticity. The treatment area see more larger units being converted into smaller units, and the units are in general see increases in price coefficients. In short, we expect more small units and at more expensive price range appear in the treatment area.

In the control group, the changes are flatter, where we see variations in total price effects across all price range. While we observe the same effects of structural characteristic changes and the price coefficient changes in the area, but the magnitude is relatively smaller than found in the treatment area. The results imply that the opening of CCL create significant effects that cause not only price elasticity effects, but also compositional changes in the housing market in the areas within 600m from the CCL MRT stations.

6. Conclusion

This paper makes two significant extensions to Diao, Leonard and Sing (2017) that study the capitalization effects of the CCL opening. They show that the use of network distance, and the log-polynomial regression could be more precisely calibrate the treatment zone, and then they apply the spatial autoregressive DID model showing that the ATE is smaller, but still significant, after adjusting for the spatial dynamics in local areas after the opening of the CCL.

First, we use the same CCL opening in our quasi-experiment, but make two extensions in our study, and affirm the early finding of positive capitalization effects of the CCL opening. In the OLS baseline DID mode, we find that the ATE associated with the opening of CCL is estimated at about 8.96%. However, we also show significant distributions in the treatment effects in the QDID model. The stronger effects are found in the 50th quantile houses with the treatment effect of 9.26%, whereas the treatment effect are smaller in the 10^{th} and 90^{th} quantiles at 4.14% and 6.56%, respectively. When we adjust for spatial spillover in the model, the same distributional effects are still observed, but the magnitude of QTE is smaller taking into account the spatial spillovers.

Second, we use the conditional quantile decomposition procedures proposed by Machado and Mata (2005), which is also used by McMillen (2008) to decompose the QTE to the portion that are associated with structural (variable) changes and price elasticity (coefficient) changes. We find that the total effects are not only stronger in the treatment zone, but we also find both compositional changes in the housing market and price elasticity are stronger in the treatment area relative to the control area. The results show that both compositional changes and price elasticity changes contribute to the total treatment effects. The CCL treatment causes more compositional changes where more large houses (90% quantile) are displaced by small size houses (10% quantile), but the price elasticity for the houses in the treatment areas also increases significantly. In short, the houses in the CCL treatment area become smaller, but more expensive after the opening of the CCL; but the effects are weaker in the control area.

More empirical tests could be conducted in the future to further examine if more low and medium-income households have since moved closer to the MRT stations, whereas high-income households who have stronger reliance on cars may have moved further away from the MRT station. If the QTE results show not only the housing choice by the low- and medium households, but also their tradeoff by paying MRT accessibility premiums for high car-ownership costs, one implication for urban planners is to review the carpark provisions for new non-landed private residential development in the areas near MRT stations. If these households use MRT for commuting, and do not own cars, urban planners could allow developers to convert some of the carpark space for other usable floor space.

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Table 1: Summary Statistics

	Full Sample		Treatment Group				Control Group			
			Before Treatment		After Treatment		Before Treatment		After Treatment	
Observation	21,954		3,633		3,755		7,945		6,621	
	Mean	S.D.	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
Price per housing unit (S$)	1,402,168	985,590	1,235,567	691,279	1,146,814	539,671	1,720,472	1,257,157	1,256,449	838,070
Price per square metre (S$/m2)	12,234	3,971	11,632	3,876	11,752	2,773	13,095	4,772	11,806	3,310
Ln Price	13.999	0.552	13.909	0.485	13.881	0.379	14.187	0.594	13.889	0.556
Ln Floor Area	4.640	0.492	4.607	0.459	4.539	0.408	4.776	0.476	4.551	0.532
Floor Level	7.799	6.151	8.195	6.025	9.680	6.424	6.834	5.941	7.673	6.046
Property Type										
Apartment	0.371	0.483	0.390	0.488	0.403	0.491	0.282	0.450	0.448	0.497
Condominium	0.623	0.485	0.610	0.488	0.597	0.491	0.713	0.452	0.538	0.499
Executive Condominium	0.006	0.078	0.000	0.000	0.000	0.000	0.005	0.071	0.014	0.119
Property Lease Type										
Freehold	0.512	0.500	0.445	0.497	0.255	0.436	0.630	0.483	0.553	0.497
Leasehold	0.488	0.500	0.555	0.497	0.745	0.436	0.370	0.483	0.447	0.497
Purchaser Type										
HDB	0.323	0.468	0.304	0.460	0.379	0.485	0.234	0.424	0.408	0.492
Private	0.677	0.468	0.696	0.460	0.621	0.485	0.766	0.424	0.592	0.492
Sale Type										
New Sale	0.512	0.500	0.496	0.500	0.571	0.495	0.457	0.498	0.552	0.497
Sub Sale	0.082	0.275	0.119	0.324	0.058	0.234	0.078	0.268	0.081	0.273
Resale	0.406	0.491	0.385	0.487	0.371	0.483	0.465	0.499	0.367	0.482
Network Distance to MRT (m)	803.193	397.163	418.035	126.353	335.457	159.003	1054.922	307.053	977.734	273.545
Euclidean Distance to MRT (m)	490.773	309.308	245.221	101.232	195.593	116.393	647.842	291.381	604.439	277.544
Distance to School (km)	1.667	688.148	1.413	0.745	1.641	0.638	1.685	0.697	1.800	0.631
Distance to CBD (km)	6.014	1647.860	6.140	1.588	6.416	1.416	5.599	1.625	6.216	1.722
Distance to Expressway (km)	1.111	663.418	1.162	0.597	1.024	0.497	1.034	0.733	1.227	0.673
Distance to Bus Stop (km)	0.158	97.852	0.140	0.056	0.131	0.075	0.182	0.117	0.154	0.095
Distance to Mall (km)	1.835	880.697	2.221	0.905	1.591	0.770	2.008	0.888	1.553	0.781

Table 2: Unconditional Quantile Distributions of Log-Housing Prices

	Treatment Group		Control Group		Differences		Difference in Differences
	Before Treatment (1)	After Treatment (2)	Before Treatment (3)	After Treatment (4)	[(2)-(1)] (5)	[(4)-(3)] (6)	[(5)-(6)] (7)
Ln Price (Mean)	13.909	13.881	14.187	13.889	-0.027	-0.298	0.271
Ln Price (Median)	13.856	13.869	14.159	13.854	0.013	-0.305	0.318
Ln Price (10th percentile)	13.299	13.375	13.479	13.141	0.076	-0.338	0.414
Ln Price (25th percentile)	13.551	13.635	13.767	13.517	0.084	-0.250	0.334
Ln Price (75th percentile)	14.213	14.095	14.561	14.229	-0.118	-0.332	0.214
Ln Price (90th percentile)	14.597	14.331	14.934	14.635	-0.266	-0.299	0.033
Observation	3,633	3,755	7,945	6,621			

Table 3: Quantile Treatment Effects

	OLS			Quanile 0.1			Quantile 0.5			Quantile 0.9		
	Coef.	Std. Error		Coef.	Std. Error		Coef.	Std. Error		Coef.	Std. Error	
(Intercept)	10.4001	0.0284	***	10.4413	0.0352	***	10.3343	0.0337	***	10.3509	0.0325	***
Within 600 m of CCL station x Post operation	0.0896	0.0054	***	0.0414	0.0051	***	0.0926	0.0042	***	0.0656	0.0054	***
Within 600 m of CCL station	0.0196	0.0040	***	0.0388	0.0038	***	0.0229	0.0034	***	0.0049	0.0047	
Post operation	-0.0348	0.0053	***	-0.0414	0.0044	***	-0.0449	0.0055	***	-0.0263	0.0064	***
ln(property_area)	0.8668	0.0029	***	0.7811	0.0030	***	0.8621	0.0025	***	0.8908	0.0031	***
Level	0.0066	0.0002	***	0.0066	0.0002	***	0.0068	0.0001	***	0.0071	0.0003	***
factor(PROPERTY_TYPE) Condominium	0.1147	0.0031	***	0.1733	0.0033	***	0.1114	0.0032	***	0.0621	0.0035	***
factor(PROPERTY_TYPE) EC	0.1184	0.0170	***	0.2087	0.0228	***	0.1320	0.0098	***	-0.0451	0.0280	
FREEHOLD	0.1913	0.0033	***	0.1445	0.0032	***	0.2168	0.0031	***	0.1715	0.0043	***
factor(PURCHASER_TYPE) Private	0.0341	0.0027	***	0.0177	0.0019	***	0.0290	0.0018	***	0.0200	0.0024	***
factor(SALE_TYPE) Resale	-0.2653	0.0029	***	-0.2983	0.0030	***	-0.2604	0.0031	***	-0.2158	0.0036	***
factor(SALE_TYPE)Sub Sale	-0.0339	0.0045	***	-0.0715	0.0034	***	-0.0091	0.0044	*	-0.0276	0.0030	***
Dis_PMS30 (km)	-0.0323	0.0036	***	-0.0135	0.0040	***	-0.0319	0.0036	***	-0.0376	0.0047	***
Dis_CBD (km)	-0.1000	0.0031	***	-0.0860	0.0036	***	-0.0900	0.0038	***	-0.0636	0.0033	***
Dis_Expres (km)	0.0362	0.0029	***	0.0409	0.0033	***	0.0374	0.0027	***	0.0227	0.0038	***
Dis_bus (km)	0.4041	0.0151	***	0.3520	0.0111	***	0.3605	0.0156	***	0.4257	0.0220	***
Dis_Mall (km)	-0.0689	0.0027	***	-0.0761	0.0028	***	-0.0845	0.0031	***	-0.0814	0.0031	***
Planning area fixed effect	Yes			Yes			Yes			Yes		
Transaction quarter fixed effect	Yes			Yes			Yes			Yes		

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

Table 4: Quantile Spatial Autoregressive Treatment Effects

	Spatial IV Quantile 0.1			Spatial IV Quantile 0.5			Spatial IV Quantile 0.9		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
(Intercept)	3.1186	0.3528	***	1.5874	0.2103	***	0.6381	0.4444	
Within 600 m of CCL station x Post operation	0.0324	0.0090	***	0.0615	0.0059	***	0.0589	0.0084	***
Within 600 m of CCL station	0.0405	0.0093	***	0.0338	0.0048	***	0.0030	0.0066	
Post operation	-0.0240	0.0092	**	-0.0198	0.0061	**	-0.0010	0.0096	
ln(property_area)	0.7867	0.0057	***	0.8736	0.0035	***	0.8995	0.0052	***
Level	0.0063	0.0003	***	0.0054	0.0002	***	0.0061	0.0004	***
factor(PROPERTY_TYPE) Condominium	0.1476	0.0076	***	0.0563	0.0044	***	0.0163	0.0067	*
factor(PROPERTY_TYPE) EC	0.0107	0.0215		-0.1051	0.0150	***	-0.2199	0.0229	***
FREEHOLD	0.1522	0.0078	***	0.1857	0.0042	***	0.1637	0.0061	***
factor(PURCHASER_TYPE)Private	0.0163	0.0030	***	0.0222	0.0023	***	0.0177	0.0032	***
factor(SALE_TYPE)Resale	-0.2910	0.0086	***	-0.2516	0.0036	***	-0.1961	0.0062	***
factor(SALE_TYPE)Sub Sale	-0.1034	0.0113	***	-0.0136	0.0054	*	-0.0107	0.0060	.
Dis_PMS30 (km)	0.0140	0.0105		-0.0007	0.0047		-0.0534	0.0118	***
Dis_CBD (km)	-0.0202	0.0064	**	-0.0152	0.0046	***	-0.0561	0.0091	***
Dis_Expres (km)	0.0035	0.0058		-0.0083	0.0033	*	0.0145	0.0078	.
Dis_bus (km)	0.4414	0.0302	***	0.4118	0.0187	***	0.3832	0.0291	***
Dis_Mall (km)	-0.0694	0.0047	***	-0.1006	0.0034	***	-0.0932	0.0051	***
wy	0.5000	0.0233	***	0.6000	0.0142	***	0.7000	0.0323	***
Planning area fixed effect	Yes			Yes			Yes		
Transaction quarter fixed effect	Yes			Yes			Yes		

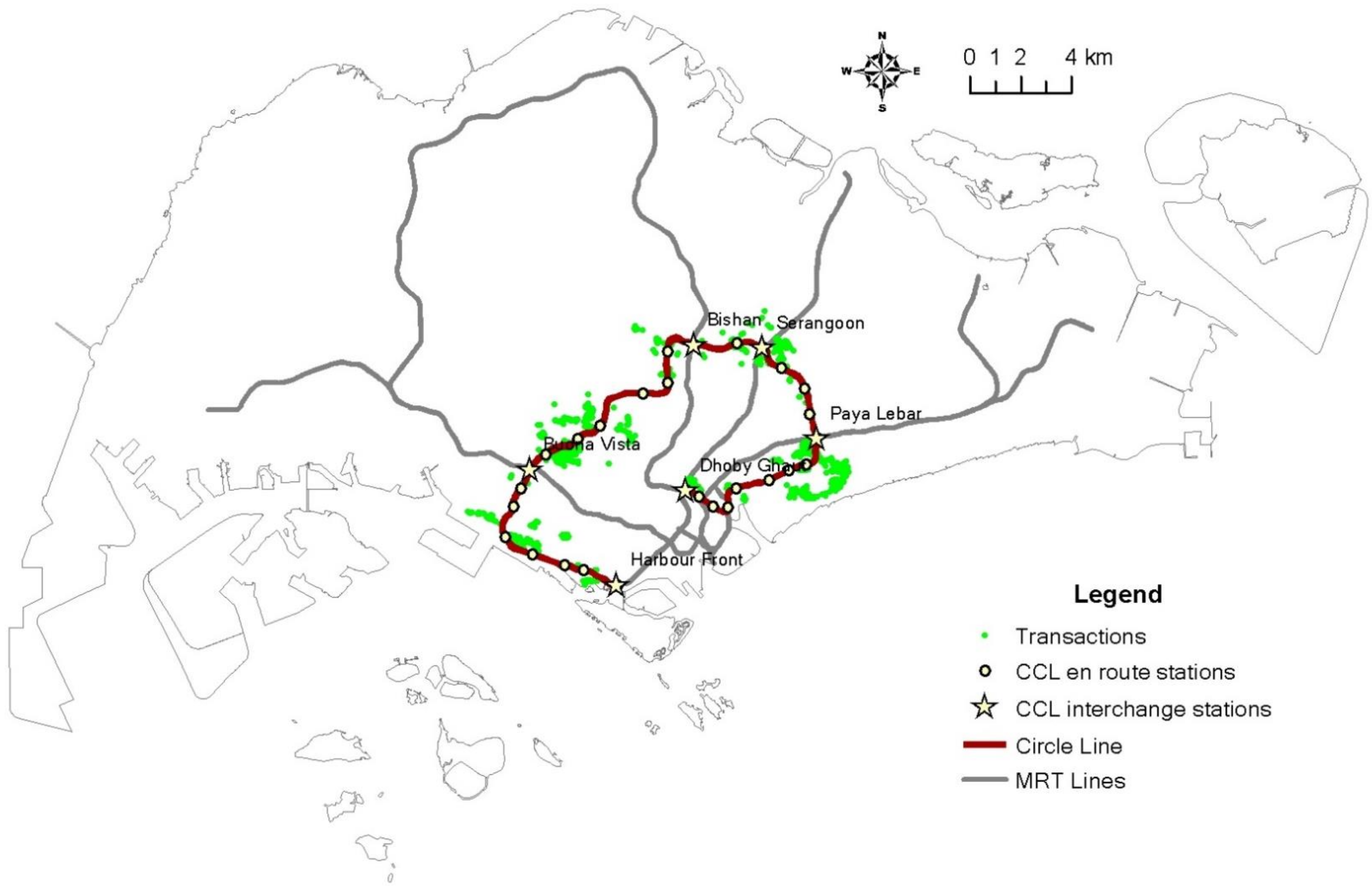
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table 5: Quantile Decomposition of Treatment Effects

	Treatment						Control					
Quantile	Total Difference		Variable Effect		Coefficient Effect		Total Difference		Variable Effect		Coefficient Effect	
0.10	0.118	***	-0.303	***	0.421	***	-0.201	***	-0.539	***	0.338	***
	(0.008)		(0.008)		(0.004)		(0.012)		(0.007)		(0.009)	
0.20	0.220	***	-0.170	***	0.390	***	-0.150	***	-0.441	***	0.291	***
	(0.009)		(0.008)		(0.005)		(0.022)		(0.023)		(0.005)	
0.30	0.193	***	-0.151	***	0.344	***	-0.077	***	-0.338	***	0.261	***
	(0.008)		(0.007)		(0.004)		(0.012)		(0.011)		(0.005)	
0.40	0.154	***	-0.178	***	0.332	***	-0.084	***	-0.320	***	0.236	***
	(0.008)		(0.008)		(0.004)		(0.012)		(0.009)		(0.005)	
0.50	0.160	***	-0.184	***	0.344	***	-0.113	***	-0.296	***	0.183	***
	(0.006)		(0.005)		(0.003)		(0.012)		(0.011)		(0.005)	
0.60	0.166	***	-0.184	***	0.350	***	-0.149	***	-0.248	***	0.098	***
	(0.006)		(0.006)		(0.004)		(0.015)		(0.012)		(0.007)	
0.70	0.176	***	-0.153	***	0.329	***	-0.191	***	-0.224	***	0.032	***
	(0.007)		(0.007)		(0.003)		(0.014)		(0.012)		(0.006)	
0.80	0.200	***	-0.120	***	0.320	***	-0.264	***	-0.230	***	-0.035	***
	(0.007)		(0.007)		(0.004)		(0.010)		(0.008)		(0.005)	
0.90	0.152	***	-0.151	***	0.302	***	-0.281	***	-0.197	***	-0.084	***
	(0.009)		(0.007)		(0.007)		(0.016)		(0.015)		(0.006)	

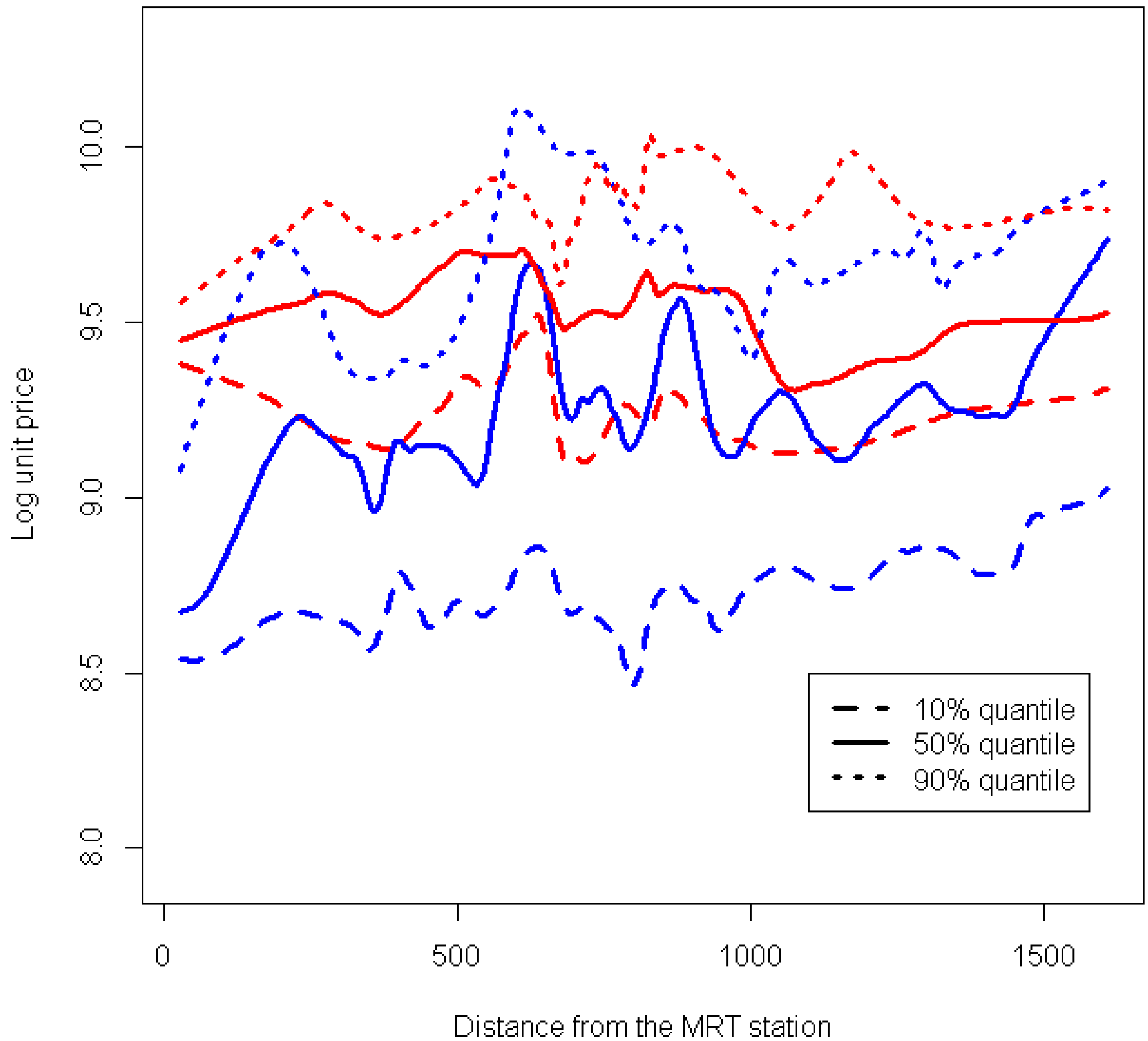
Note: *** p<0.01. Sttandard error in parenthese.

Figure 1: MRT Network and Non-Landed Private Housing Transactions



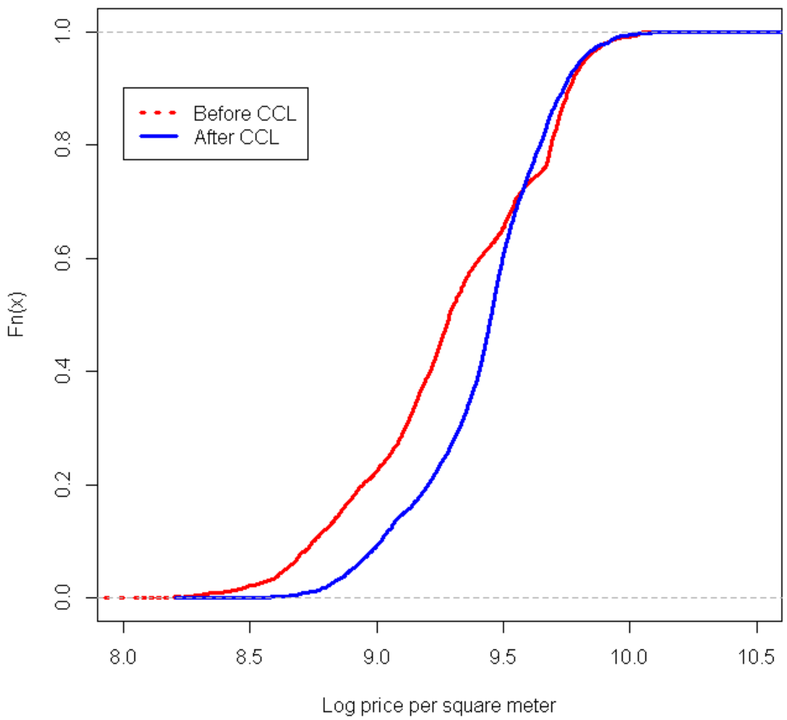
Note: The Figure shows the map of Singapore, and the darken solid (red line) shows the Circle line MRT stations on the line are represented by dot (en-route stations) and star (interchange stations); and the light green dot represent the distributions of housing samples along the Circle Line.

Figure 2: Quantile Distributions of Log-Prices

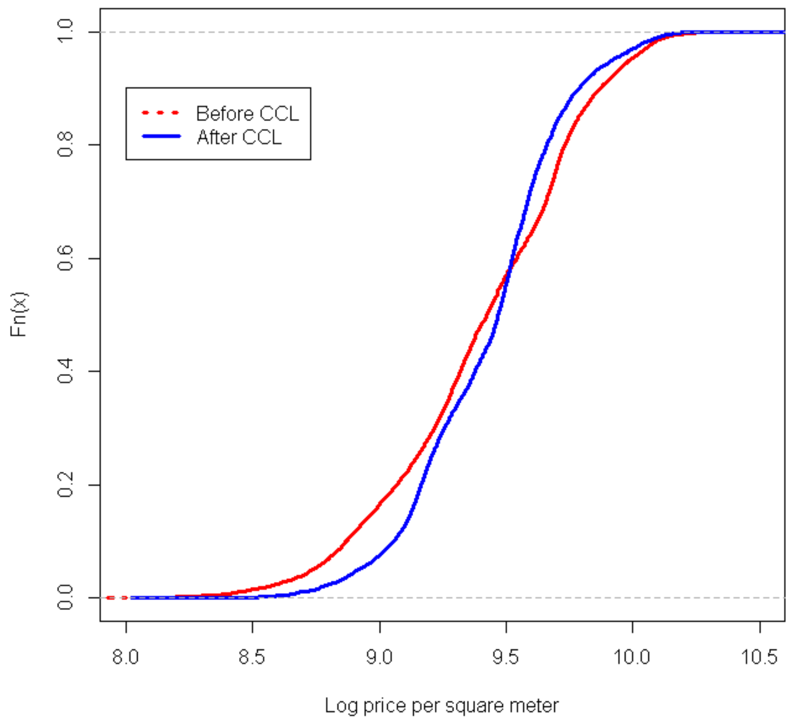


Note: Housing price gradients (Log unit price by distance from MRT station) before and after the opening of CCL generated using locally weighed quantile regressions for the 10% (denoted by the dashed curves), 50% (denoted by the solid curves) and 90% (denoted by the dotted curves) quantiles of transactions, respectively. Blue denotes before the opening of CCL and red denotes after the opening of CCL.

Figure 3: Cumulative distribution functions (CDF) of log unit price



(1) Treatment



(2) Control

Figure 4: Changes in the CDFs of log unit price before and after the CCL opening

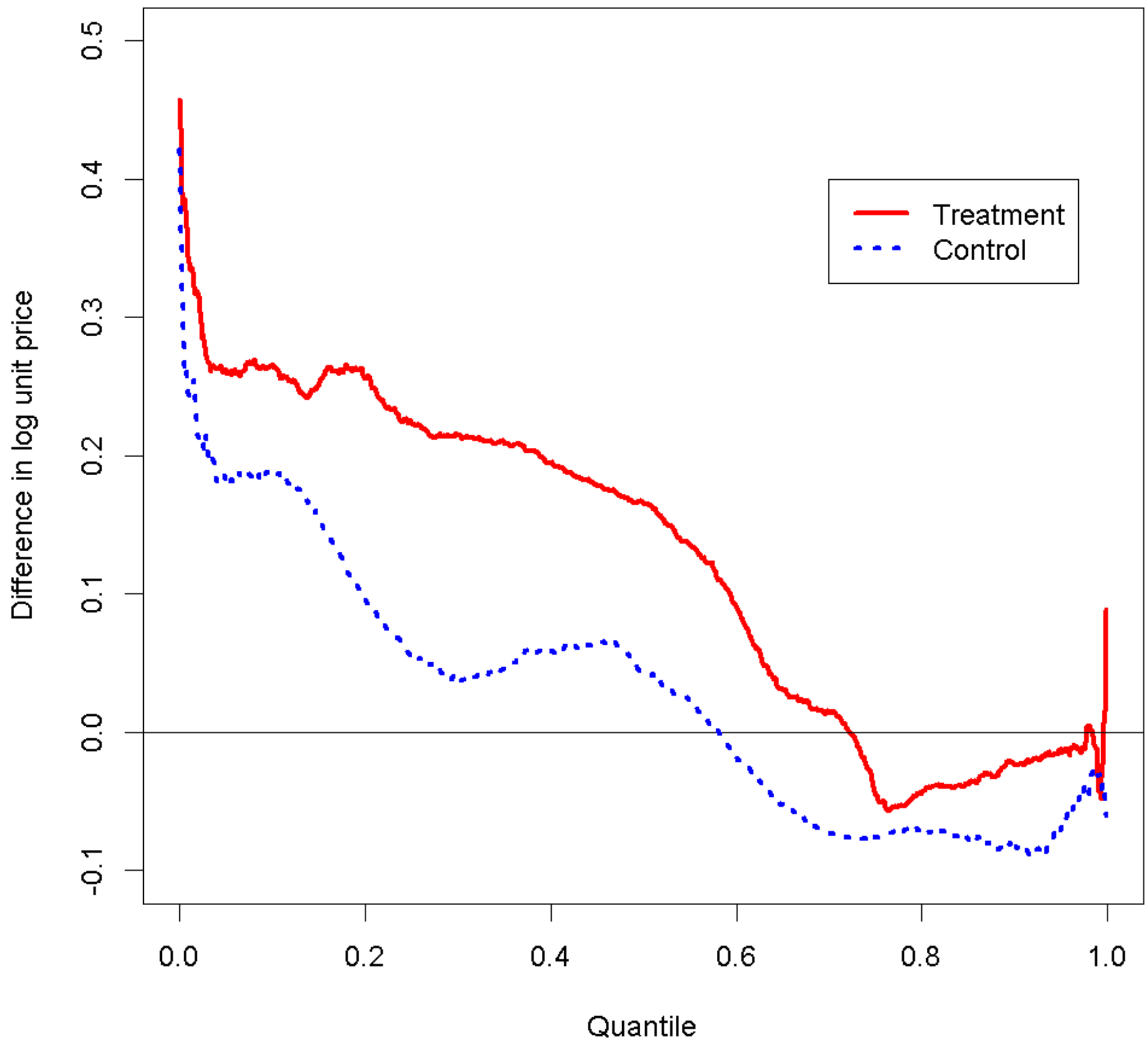
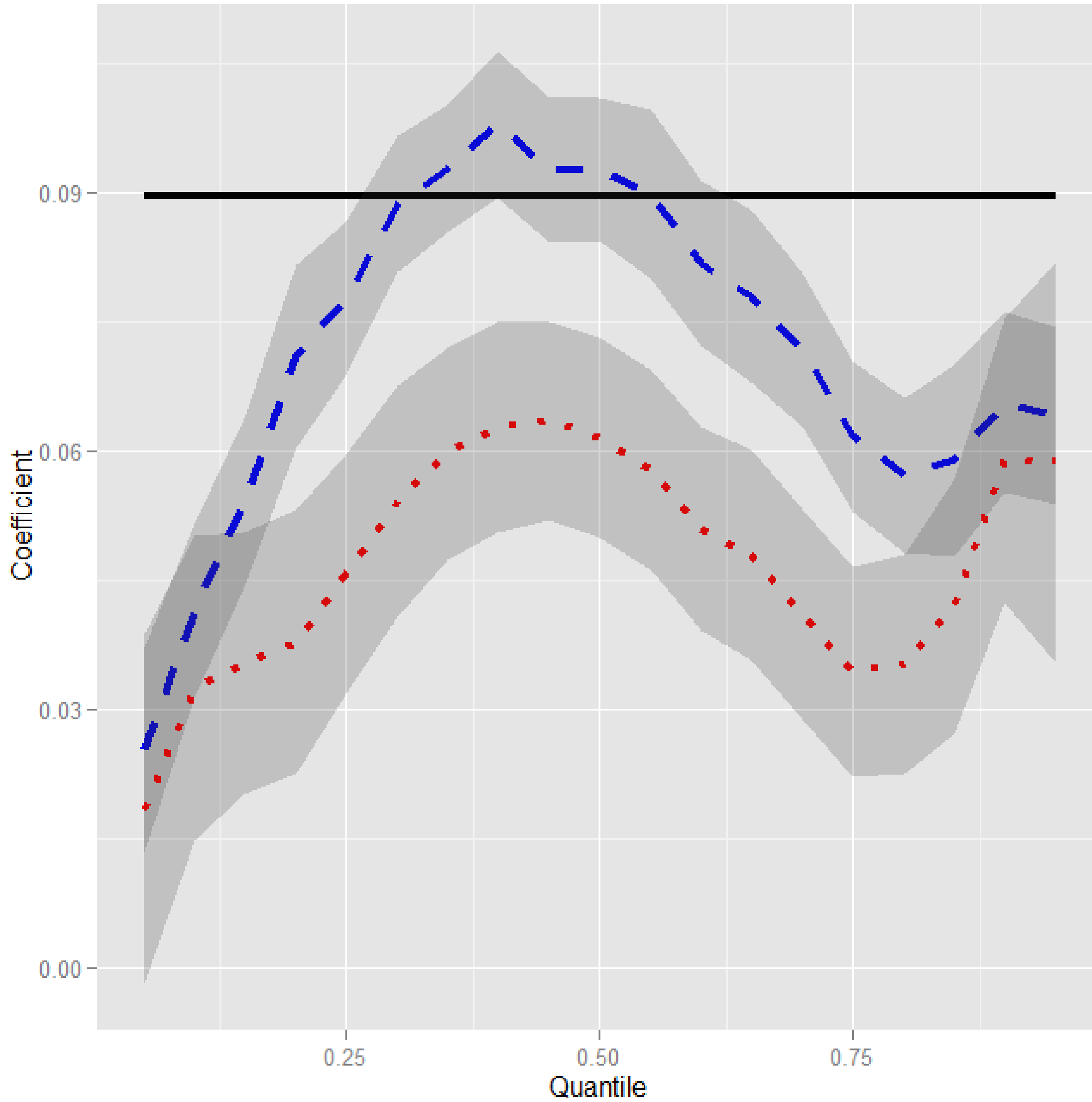


Figure 5: Quantile Distributions of Treatment Effects



Estimated coefficient for the interaction term by quantile.

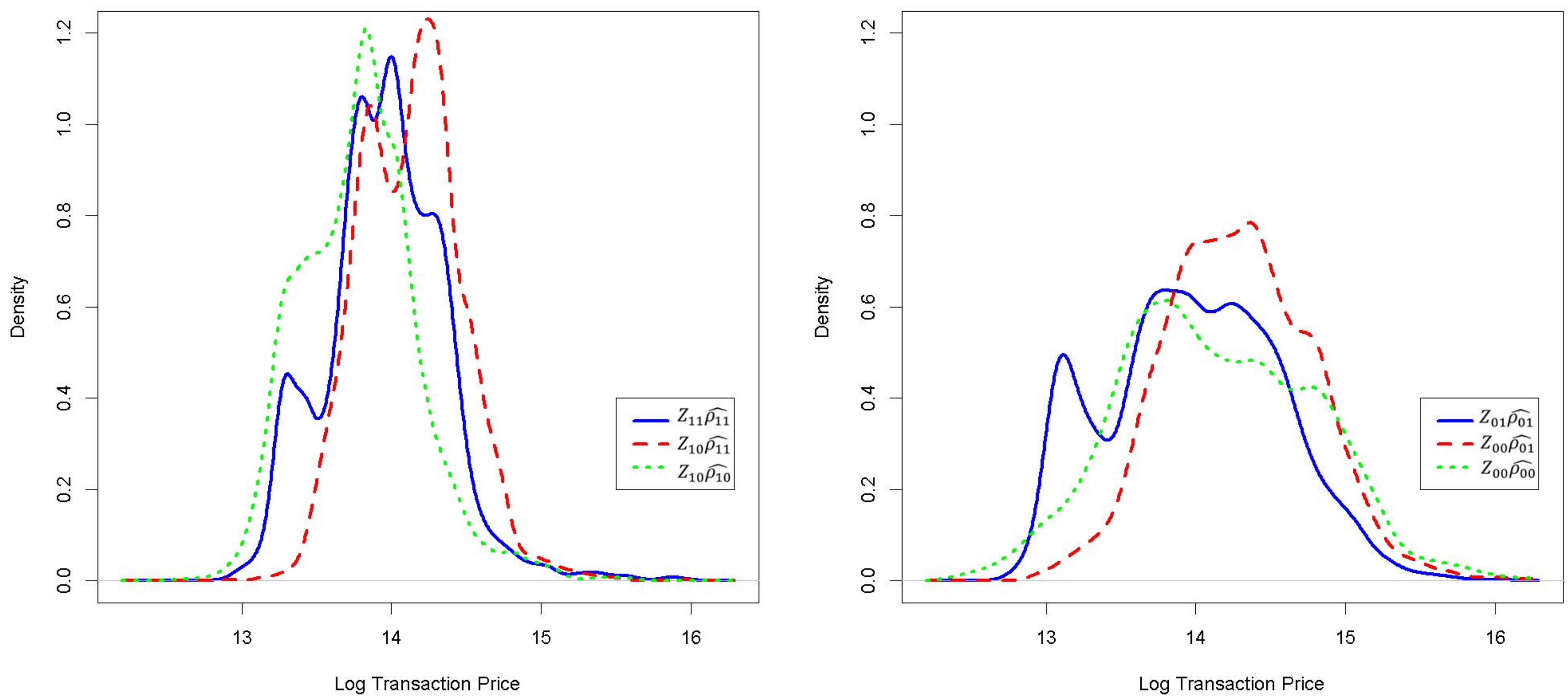
Black solid line: OLS

Blue dashed line: Quantile regression

Red dotted line: Spatial AR quantile regression

Grey band: 95% confidence interval

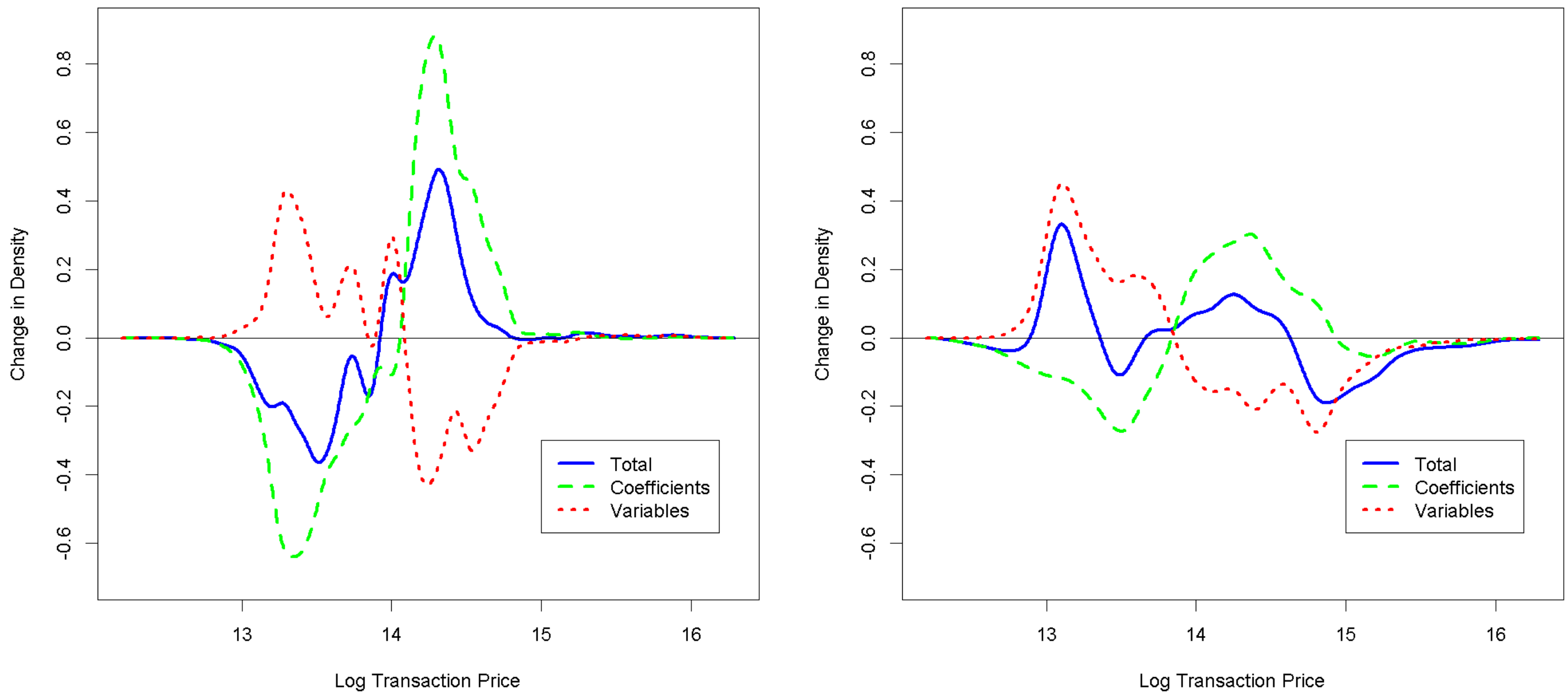
Figure 6: Density Functions for Decomposition



a) Treatment

b) Control

Figure 7: Decomposition of Density Changes



a) Treatment

b) Control

Appendix 1: 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.