The Consumer City: Evidence from Singapore

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Abstract:
Is retail dead? Using a high-resolution dataset of housing prices and self-constructed measures of proximity to amenities in Singapore across 2000-2019, I find an unchanging, if not increasing, amenity premium placed on accessibility to malls over time. This paper is the first to study temporal changes in amenity premia. It also provides a cleaner strategy to extract amenity premia than existing literature by studying Singapore, whose micro-zoning restrictions imply exogeneity in proximity measures. Using a quasi-experimental framework to test the effects of mall openings, this paper confirms empirical regularities of "anticipatory effects" and "distance decay".

1 Introduction

The rise of cities and dense urban living is a well-studied phenomenon in urban economics literature. With cities evoking pictures of over-crowdedness and unenviable living conditions, early literature understood cities from a production perspective. For example, Marshall (1890) theorised agglomeration economies which can occur through input sharing, labour market pooling and knowledge spillovers while Jacobs's (1961) idea of spatial concentration facilitating unplanned or random interactions contributed to the theory of knowledge spillovers.

Yet, today's cities evoke a very different picture from the likes of industrial Manchester and Liverpool. Cities in the developed world are valued as centres of leisure and consumption, evoking images of beautiful and well-manicured streets, large public spaces

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and varied forms of entertainment. Advances in transportation have made it easier to move factories out of cities, and production need not be concentrated in cities. There is a corresponding rise in "leisure pursuits" and cities are increasingly seen as hubs of consumption, with individuals attracted to the amenities they provide (Glaeser et al., 2001; Lloyd and Clark, 2001). Unlike production, which can be moved out of cities and transported quickly to where demand is, certain consumption experiences such as dining at foreign restaurants, catching a play, shopping at branded outlets cannot be easily replicated in areas of low demand. Rather, such experiences thrive in cities—hubs of concentrated demand—giving rise to the "Consumer City".

The "Consumer City" literature builds on the spatial equilibrium framework to study how accessibility to consumption amenities[1] and other micro-urban amenities[2] contribute to the attractiveness of cities. A spatial equilibrium arises when there are no gains from changing locations (Glaeser, 2008). Holding income constant, equilibrium housing prices should therefore capture homeowners' marginal willingness to reside in a specific place. This marginal willingness-to-pay (MWTP), following hedonic price theory (Rosen, 1974), reflects one's MWTP for underlying characteristics bundled with the house, thereby allowing us to extract the premium placed on accessibility to amenities from housing prices.

This paper uses housing prices in the resale flat market in Singapore between 2000 and 2019 to extract the premia homeowners place on accessibility to shopping malls and other micro-urban amenities—MRT (subway) stations, parks, community clubs (CCs) and schools—and studies how these premia have evolved over time. To nuance the spatiotemporal dynamics of the amenity premium placed on consumption specifically, this paper also tests the effects of mall openings on housing prices using a quasi-experimental empirical design.

This paper presents four contributions to literature:

1. I construct a novel dataset that draws information from dated maps and sources and travel duration data from Google Maps. This involves producing a complete list of malls, MRT stations, parks, CCs and schools, when they opened (and closed) to construct proximity measures across a 20-year period. While the urban economics and real estate literature has produced similar proximity measures, studies often cover short periods of time (1-2 years). After all, it is difficult to construct data across a longer timeframe as the amenities present in a geographic area change over time. On

[1] E.g. restaurants, malls

[2] E.g. transportation, green spaces, civic spaces, schools

top of the Euclidean distance (ED)[3] to the nearest amenity, I extract travel duration data from Google Maps. While a similar study (Cao et al., 2019) constructs travel duration measures using data on smartcard transactions, higher resolution data from Google Maps should improve the efficiency of estimation.

2. With 20 years of data, I study temporal changes in the amenity premia. While the literature strongly suggests that consumption amenities make cities more attractive, the closure of malls and high vacancy rates in brick-and-mortar stores in the last 5-10 years may suggest a different story. Therefore, this study answers an important question of how homeowners' preferences for malls and other micro-urban amenities have changed over time.

3. I address endogeneity, often the biggest challenge in existing literature, with a case study relatively free of endogeneity—Singapore. Existing work finds that accessibility to micro-urban amenities correlate well with the growth of cities and housing prices. Such studies generally use multivariate OLS and suffer from reverse causality and omitted variable bias. However, extensive micro-zoning restrictions in Singapore imply that measures of proximity to amenities are likelier to be exogenously determined by the government, circumventing concerns of endogeneity.

4. This paper is the first to test the effects of mall openings under a quasi-experimental setting in Singapore. While there are studies on the effects of mall construction on housing prices in other cities, this paper goes one step further to study the effects of both construction and *renovations* on housing prices, since the latter affects the quality of the amenity rather than accessibility to the amenity.

The paper proceeds as follows: Section 2 reviews the theoretical underpinnings and empirical progress in the literature, and the background of Singapore. Section 3 outlines the construction of the dataset and choice of variables. Sections 4 and 5 present the empirical design and results respectively. Section 6 checks for robustness and explores heterogeneity. Section 7 concludes.

[3]Straight-line distance between two coordinates

2 Literature Review

2.1 Spatial Equilibrium and Hedonic Pricing

The "Consumer City" literature is grounded in a no-arbitrage spatial equilibrium framework. Formally, the indirect utility function related to location choice $V(\cdot)$ is

$$V(w, r, s) = k,\ \frac{\partial V}{\partial w} > 0,\ \frac{\partial V}{\partial r} < 0,\ \frac{\partial V}{\partial s} > 0 \tag{1}$$

where w, r, s refer to income/wages, housing costs and amenities respectively (Rosen, 1979; Roback, 1982). Since individual utilities are equalised in spatial equilibrium, spatial variation in amenities implies an offsetting spatial variation in income and/or housing prices. This framework motivates a hedonic pricing model (Rosen, 1974) where housing prices capture individuals' MWTP for location-specific amenities (*amenity premia*).

The Rosen-Roback framework is key in understanding housing prices and locational choices *across* cities but it assumes that amenities are exogenous which is problematic in a within-city context. Brueckner et al. (1999) argue that many "modern amenities"[4] are dependent on economic conditions and local income level, motivating an assumption that the marginal valuation of amenities rises sharply with income. While the authors investigate how this specific assumption can explain different within-city location patterns theoretically, the paper raises a more general point that amenities are endogenous, an issue that is insufficiently tackled in empirical literature (Section 2.3).

Glaeser (2008) also notes that a key difference in within-city empirical work is the assumption of constant wages. Ostensibly, this assumption results from data sparsity—whereas income data may be easily available at the city level, it is less so at lower levels of spatial aggregation. However, including neighbourhood fixed effects[5] in a regression should account for variation of affluence across neighbourhoods.

2.2 Consumer City and Lifestyle Amenities

While Roback (1982) and earlier research (Blomquist et al., 1988; Gyourko and Tracy, 1991; Hoehn et al., 1987) measure location-specific amenities in terms of crime, pollution, weather and population density, Glaeser et al. (2001) introduce the idea of a "Consumer City", arguing that consumption amenities drive the growth of cities. The "Consumer

[4] E.g. restaurants, theatres, pools

[5] I.e. a within-neighbourhood framework

City" paradigm encompasses a whole range of micro-urban amenities, extending beyond consumption goods and services to include transportation (Diao et al., 2017), nature (Gibbons et al., 2014), civic spaces (Andersson and West, 2006) and schools (Agarwal et al., 2016). While Glaeser et al. (2001) regress county growth on amenity measures, other studies regress housing prices on amenity measures to extract the amenity premia (Gabriel and Rosenthal, 2004; Andersson and West, 2006). Using housing prices also allows for more granular analyses as data is available at higher spatial resolution.

To construct accessibility measures for micro-urban amenities (*amenity measures*), two broad approaches are taken. The first measures the density of amenities within a geographic boundary (Glaeser et al., 2001; Gibbons et al., 2014). The second measures the proximity of each home to the nearest amenity (Andersson and West, 2006; Jang and Kang, 2015). Both measures implicitly assume homogeneous amenities. While certain studies account for heterogeneity,[6] homogeneous amenities is generally assumed given data limitations.

Proximity measures, unlike density measures, implicitly allows for *spatial externalities*—the spatial reach of each amenity extends beyond arbitrary administrative boundaries. Insofar as amenities are highly substitutable, which follows from assuming homogeneous amenities, density matters less than the specific distance to an amenity. Hence, proximity is the preferred measure.

To measure proximity, many studies use the shortest Euclidean distance (ED) between homes and amenities. However, since moving between two points in a straight line is unlikely, some advocate travel duration measures (Shahid et al., 2009; Lu et al., 2014). To predict Singapore housing prices, Cao et al. (2019) employ a large dataset of smartcard transactions on public transport to construct measures of travel duration between homes and amenities. However, they conduct their analysis at the motor traffic zone (MTZ) level[7] given insufficient data to confidently model the duration between any two points. In other words, they reduce noise by sacrificing the heterogeneity between different locations within the same MTZ. Therefore, although ED only approximates true proximity, duration-based measures are imprecise too. Rather, ED is easily calculable and a useful rule-of-thumb for potential homeowners to gauge the proximity of amenities, particularly those in the neighbourhood.

[6]Song and Sohn (2007) construct a composite amenity measure for malls that includes floor area.
[7]Lower spatial resolution

2.3 Unaddressed Gaps

The first problem is the static nature of the studies. Generally, studies use data on amenities in one year to explain growth in subsequent decade(s) (Glaeser et al., 2001; Carlino and Saiz, 2019) or contemporaneous housing prices (Jang and Kang, 2015; Zhang et al., 2019). However, they do not study temporal changes in the importance of amenities. This is important: although the literature argues that cities are becoming more consumption-oriented, the rise of e-commerce (J.P. Morgan, 2019), meal delivery services (Woo, 2018) and video-streaming (Yoon, 2019) may affect the importance of consumption and other micro-urban amenities.

The second problem is endogeneity. There may be unobserved/omitted area characteristics (e.g. jurisdictional differences, aesthetics) which control for both housing prices and amenities in the area, generating *omitted variable bias*. High housing prices, which promises high-income clientele, may also attract amenity "providers" to set up shop, generating *reverse causality*.

To minimise unobserved heterogeneity, some researchers use a within-city framework where jurisdictional differences, for instance, are unlikely to differ much (Glaeser, 2007). This framework has been replicated in many cities—Hillsboro (Song and Sohn, 2007), Seoul (Jang and Kang, 2015) and Hangzhou (Zhang et al., 2019). However, there may still be significant unobserved heterogeneity which correlates with both housing prices and accessibility to amenities across neighbourhoods in the same city, motivating the within-neighbourhood framework taken here.

To tackle reverse causality, Carlino and Saiz (2019) instrument accessibility to amenities with the number of tourist trips and number of crowdsourced picturesque locations, finding that accessibility to amenities explain US urban population growth well. However, the paucity of similar work with housing prices suggests, as we expect, difficulties in finding good instruments.

A quasi-experimental framework may also tackle endogeneity. For instance, Agarwal et al. (2016) study the effects of school relocation on housing prices in Singapore using a quasi-experimental framework. They find that the relocation of a "top primary school" leads to price increases among properties within the new catchment area for priority enrollment,[8] and price declines in the original catchment area.

Similarly, Diao et al. (2017) study the effects of a new MRT network on Singapore housing

[8] Within 2km of the school

prices. Since train stations in Singapore do not have clearly demarcated catchment areas unlike primary schools, the authors construct housing price gradients (against distance to the nearest new station) before and after the opening of the stations to identify discontinuities in the gradients.[9] A discontinuity yields an approximation of stations' "catchment area", where there is a substantial price premium arising from proximity to the amenity. Beyond estimating the spatial distribution of amenity premia, they find "anticipatory effects"—prices rising even before stations open. Insofar as treatment is exogenous conditional on other included covariates (*unconfoundedness*), a quasi-experimental framework yields unbiased estimates and elucidates the spatiotemporal dynamics of amenity premia. While this is not argued in either studies, the centrally planned micro-zoning restrictions in Singapore provides a reasonable exogeneity argument.

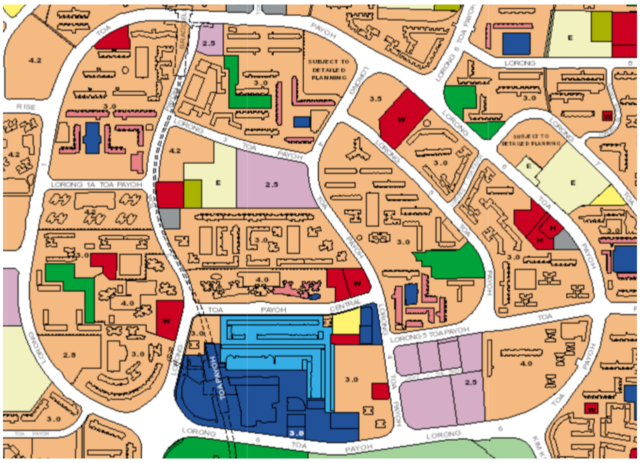
2.4 The Case of Singapore

Singapore is a city-state where each lot of land is centrally assigned a specific purpose (e.g. residential, commercial, mixed-use, transportation) by the Urban Redevelopment Authority (URA, 2019). More than 80% of the resident population lives in public housing estates constructed by the Housing and Development Board (HDB, 2020). HDB constructs these estates from scratch[10] in accordance with URA restrictions. Hence, there is a common template across public housing estates in Singapore (FIGURE 1), comprising a town centre, where malls and key transportation infrastructure are located, parks, CCs and schools. The proximity between a lot assigned for a specific amenity and flats in the neighbourhood is predetermined by URA and is unlikely to be influenced by housing prices. At such a low (spatial) level of analysis,[11] it is also unlikely for unobserved within-neighbourhood variation to correlate with both housing prices and URA's planning decisions. Therefore, in an OLS regression of housing prices against measures of proximity to amenities, these amenity measures satisfy the exogeneity assumption and will yield unbiased estimates of the amenity premia.

[9] Prices are smoothened with a local polynomial regression.

[10] Unlike many cities where construction follows path dependency, almost all public housing estates in Singapore were constructed from scratch in post-independence Singapore.

[11] The average area of each neighbourhood is 7km^2.



Legend: Dark Blue (Commercial); Red (Civic Spaces);
Green (Parks); Grey (Transport); Orange (Residential)

Figure 1: Toa Payoh Town Plan (URA, 2019)

In a quasi-experimental framework, exogeneity in an amenity's location implies exogeneity in the catchment area, and treatment is thus unconfounded. While Agarwal et al. (2016) and Diao et al. (2017) study treatment effects of school relocation and MRT network construction, the effects of mall openings on housing prices in Singapore has not been studied. Therefore, beyond a baseline OLS regression of housing prices against amenity measures, this paper studies the effects of mall openings under a quasi-experimental framework.

3 Data

The dataset of resale flat transactions for 2000-2019 is taken from HDB and totals over 500,000 transactions. It includes each flat's price, address, postal code, neighbourhood and inherent characteristics—flat model, number of rooms, size and the floor level (given as a range).[12]

I use proximity to measure accessibility to amenities since it is reasonable to assume amenity homogeneity in Singapore—the quality of public infrastructure is fairly homogenised[13] while malls follow a similar template (Davies, 2012).[14] The choice of amenities in this paper (malls, MRT stations, parks, CCs and schools) follows aspects commonly studied in the literature. Other common amenities (e.g. crime, pollution, weather, aesthetics) are either omitted since Singapore is a small city-state with negligible variation in these aspects or controlled with neighbourhood fixed effects. While studies emphasising consumption construct several measures for specific consumption amenities (e.g. supermarkets, restaurants, cinemas), the vast majority of consumption amenities in Singapore are housed in malls (Davies, 2012). Therefore, I construct a single measure for parsimony.

To construct the amenity measures, I compiled lists of malls, MRT stations, parks, CCs and schools. Given the 20-year timeframe, I consulted lists of places of interests in dated maps to construct them, taking note of their addresses, when they opened and closed. I then queried the coordinates using Singapore Land Authority's OneMap API.

To measure the proximity of homes to amenities, I use Python's `geodesic` package to (1) calculate the ED between each flat and amenities in its own and contiguous neighbourhoods using their coordinates, and (2) find the distance between each flat and the nearest mall, MRT station, park and CC.

Like Cao et al. (2019), I construct travel duration measures. Given the approximations involved in their methodology, I tapped on Google Maps for higher-resolution data. Google Maps's API provides data on travel duration between any two points across three modes of transport—driving, walking and public transport. With the duration being specific to two sets of coordinates rather than two MTZs, the data is more granular. By including accurate data on driving and walking, the data is also more comprehensive.

I also construct measures of distance and duration to the Central Business District

[12] I take the upper bound of the range divided by the highest floor of the block to derive a measure of relative height.

[13] I explore heterogeneity in MRT stations as an extension.

[14] I explore heterogeneity by testing the effects of mall quality improvements (renovations).

(CBD)—Raffles Place and Central Retail District (CRD)—Orchard. While studies on housing prices generally consider CBD as a city's focal point and include accessibility to CBD in their regressions, Carlino and Saiz (2019) argue that CRD is also important. CRD, which they define as "the set of locations within a metropolitan area that is close to recreational and lifestyle amenities", will be a better reflection of a city's focal point since I hypothesise that Singapore is a "Consumer City".

Since there are three measures of duration, I construct a composite measure for parsimony. Denoting λ as the proportion of population who use public transport or walk in their daily commute, the composite measure of duration is

$$dura_c = \lambda(\min\{dura_{pt}, dura_w\}) + (1 - \lambda)dura_d \tag{2}$$

Data from the two Census (DOS, 2000; DOS, 2010) suggests $\lambda \approx 0.57$. However, the General Household Survey (2015) suggests that λ has increased to 0.67. Therefore, two composite measures are constructed—one where a common λ (set as 0.63) is used for the whole sample and one where a different λ is used before and after 2010.

For schools, since students are prioritised for admission if they live within 2km of a primary school, the specific distance from the school matters less. Therefore, I construct a dummy for the existence of a "top primary school" within 2km of the flat. I review enrolment data for 2000-2019, and created a list of the 50 most oversubscribed[15] schools. Schools that feature in my list consistently feature in the lists of top performers in primary school national examinations.[16]

Since housing prices trend upwards with inflation, I deflate prices with GDP per capita, the GDP deflator and Resale Price Index.

[15] Proxy for desirability

[16] Not published since 2011

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs.
Price (S$)	329634	142319	28000	1205000	523263
Flat Characteristics					
Ordinary	0.967	0.179	0	1	523263
Maisonette	0.029	0.168	0	1	523263
DBSS	0.002	0.048	0	1	523263
Special	0.001	0.027	0	1	523263
Terrace	0.001	0.027	0	1	523263
Floor (Ratio of Highest Floor)	0.589	0.263	0.071	1	523263
Floor Area (sqm)	96.7	25.3	28	297	523263
Measures of Accessibility (m)					
Distance to Nearest MRT	896	597	21.9	6697	523263
Distance to Nearest Mall	778	539	10.0	3570	523263
Distance to Nearest Park	1020	580	22.1	3125	523263
Distance to Nearest CC	496	289	2.01	3878	523263
Top Pri Sch within 2km	0.898	0.303	0	1	523263
Distance to Orchard	10902	3986	1321	19935	523263
Distance to Raffles Place	12300	4464	352	20042	523263
Measures of Accessibility (s)					
Duration to Nearest MRT	701	271	14.3	2337	523263
Duration to Nearest Mall	653	297	9.07	1887	523263
Duration to Nearest Park	853	363	1.00	2191	523263
Duration to Nearest CC	476	213	1.00	1907	523263
Duration to Orchard	2346	596	834	4063	523263
Duration to Raffles Place	2182	478	482	3560	523263

4 Empirical Design

4.1 Baseline Estimation

The baseline estimation is grounded in the within-city[17] spatial equilibrium framework and hedonic price theory. Holding income constant, as is commonly done for within-city analyses, the spatial equilibrium framework prescribes a positive relationship between amenities (A_{it}) and housing prices ($Price_{it}$). Including neighbourhood fixed effects (N_i) implicitly controls for variation in average income, population density, overall aesthetics, among other unobserved neighbourhood characteristics.

The baseline regression equation is:

$$\frac{Price_{it}}{P_t} = \alpha + \gamma C_{it} + \beta A_{it} + \delta N_i + \varepsilon_{it} \tag{3}$$

where P_t is a price deflator.

Table 2: Independent Variables in Baseline Regression

C_{it}	A_{it}
Flat model	Distance to nearest MRT station
Floor area (sqm)	Distance to nearest shopping mall
Floor-to-highest floor ratio	Distance to nearest park
	Distance to nearest community club
	Dummy for top primary school in 2km radius
	Travel duration to CRD

GDP per capita is used as P_t in the baseline since it proxies for purchasing power.

The similarity of certain covariates may generate multicollinearity. Specifically, since CRD and CBD are only 4 MRT stations away, proximity measures to Orchard and proximity measures to Raffles Place are highly correlated (∼0.9 for both distance and duration-based measures). Since the study is about the "Consumer City", I use CRD in the baseline.

As commercial spaces are planned to be easily accessible by MRT, many malls and stations are co-located. However, the correlation coefficients of proximity measures for malls and MRT stations are only ∼0.2, implying that multicollinearity is unlikely to be a problem. In any case, I isolate the amenity premium placed on consumption from other amenity premia using a quasi-experimental framework (Section 4.2).

[17] "Within-*neighbourhood*" is more accurate, given neighbourhood fixed effects.

In the baseline, I use ED for malls, MRT stations, parks and CCs since these are often within walking distance from each flat and ED is a reasonable approximation. ED is especially applicable to Singapore as HDB flats have "void decks" where the ground floor of each building allows for thoroughfare. Duration is used for CRD as getting there involves longer journeys, and the composite measure with a standardised λ is used in the baseline.

All continuous variables are expressed in logs—estimated coefficients can be interpreted as elasticities. I run a regression for each year of data to derive coefficients for each year. A negative coefficient implies a positive amenity premium, arising from convenient access. Conversely, a positive coefficient implies a negative premium which may arise from negative externalities. After all, CCs and shopping malls are hubs of activities while train stations generate traffic and noise in the vicinity. Therefore, estimated coefficients capture net effects and there is no compelling reason to hypothesise the coefficients' signs *ex ante*.

Following hedonic price theory, I control for flat characteristics (C_{it})—relative height of the unit, floor area and flat model.

4.2 Effects of Mall Openings

Between 2011 and 2019, there were 59 mall openings in Singapore, comprising both new and newly renovated malls. Construction of new malls in Singapore is initiated by Government Land Sales of land plots assigned for commercial/mixed-use. The construction of new malls on lots exogenously determined by URA is a treatment on the accessibility to amenities of flats lying within an arbitrary catchment area vis-à-vis flats outside the catchment area. The renovation of malls offers a different interpretation—it augments the quality of amenities already accessible to flats within the catchment area. When a mall undergoes renovation depends more on the mall's age than housing prices or other unobserved heterogeneity between the treatment and control groups. Hence, treatment is also exogenously assigned for the renovation of new malls.

I focus on malls outside CBD/CRD since there are too few flats in CBD/CRD for meaningful analysis. Among newly renovated malls, I only include major renovations.[18] In total, there are 9 newly constructed and 8 newly renovated malls in the sample.

Following Diao et al. (2017), I graph housing prices (per m^2), smoothed with a local

[18] ≥ 1 year of closure

polynomial regression of degree zero[19] against ED of the flat to a newly opened mall, both before and after the mall's opening month. This offers a first pass at checking if mall (re)opening yields any effects on prices and whether the effects attenuate with distance, providing an approximation of the catchment area's radius.

To minimise confounding effects, I follow Diao et al. (2017) in restricting the study area. I choose a cut-off radius of 1.5km because 90% of flats in the dataset lie within 1.5km from a mall[20] and including flats too far away from the mall of interest will make flats in the treatment and control groups less comparable, confounding estimates. I restrict the sample to a ±4-year period around the opening month as new mall projects within the sample are announced ∼3-4 years before the mall opens. For newly renovated malls, I use a ±2-year period because the sample includes malls that reopened 2 years before my dataset's cut-off date—restricting the sample period allows for greater balance in data before and after the opening month. Furthermore, renovations tend to have a shorter timeframe than construction—works are usually announced 2 years in advance and completed over ∼1 year.

Denoting the catchment area's radius as D_c and D_r for newly constructed and newly renovated malls respectively, I construct two dummies:

$$Post_k = \begin{cases} 1 & \text{if flat is sold after or on the opening month of the mall} \\ 0 & \text{if flat is sold before the opening month of the mall} \end{cases} \tag{4}$$

$$Treat_k = \begin{cases} 1 & \text{if flat lies within and including } D_k \text{ m of the mall} \\ 0 & \text{if flat is more than } D_k \text{ m away from the mall} \end{cases} \tag{5}$$

where $k \in \{c, r\}$. I then specify a difference-in-difference model

$$\begin{aligned} Price_{it} = \alpha &+ \beta_1 Post_{kit} + \beta_2 Treat_{kit} + \beta_3 Post_{kit} \times Treat_{kit} \\ &+ \gamma C_{it} + \theta A_{it} + \delta N_i + \zeta T_t + \varepsilon_{it} \end{aligned} \tag{6}$$

All continuous variables are expressed in logs. C_{it} and N_i are the same as before but A_{it} no longer includes proximity to malls to avoid multicollinearity with the treatment dummy. Time fixed effects T_t are included since they are not as strongly correlated with $Post_{kit}$[21] and there are often important uncaptured time dynamics for housing prices. I estimate separate regressions for $k \in \{c, r\}$.

[19] Taking the moving average

[20] The median minimum distance is only 658m.

[21] Whether a transaction at time t yields $Post_{kit} = 1$ depends on when the mall opens too but if a flat's minimum distance to a mall exceeds D_k, then $Treat_{kit}$ almost surely $= 0$.

The coefficients of interest are β_1—effect of mall openings on the control group, β_2—amenity premium for being in the treatment group and β_3—the additional premium for being in the treatment group post-opening (*treatment effect*). Since estimated coefficients capture net effects of amenities, they could swing in either direction.

5 Results

5.1 Baseline

The baseline regression is estimated for each year (TABLE 3). FIGURE 2 graphs the coefficients of each amenity measure against time. The results show a generally positive premium placed on accessibility to malls, MRT, parks and CRD (negative coefficients) and being in a top primary school's catchment area (positive coefficient). There is a negative premium placed on accessibility to CCs. Given large confidence intervals arising from the clustered[22] robust standard errors, only the amenity premia for MRT, malls and CRD are significant across most years.

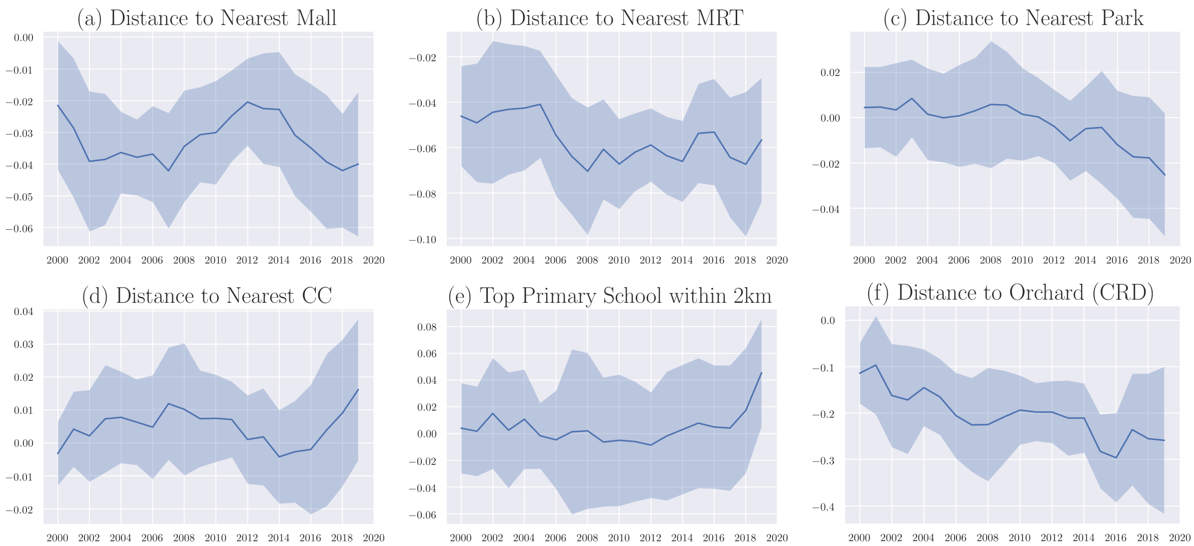


FIGURE 2: BASELINE RESULTS: COEFFICIENTS OF AMENITY MEASURES

There is no clear trend in the amenity premia for MRT and malls, and estimated coefficients in adjacent years are not statistically different from each other. An unchanging positive amenity premium for MRT is, however, not unexpected since there had not been a significant change in working patterns prior to 2020, and accessibility to transport remained essential in day-to-day life. In contrast, the rise in e-commerce and video-streaming may have made malls increasingly obsolete, suggesting a fall in the amenity premium for malls. However, the data suggests no such trend—while the premium fell after the Great Recession, it has recovered to pre-2008 levels.

The accessibility to CRD yields a positive and increasing[23] premium. While it is diffi-

[22] I cluster errors by neighbourhood.

[23] Based on point estimates alone.

cult to separately identify the effects of accessibility to retail and to CBD, the positive premium is likely resultant from both. This implies consistent, if not greater demand for accessibility to retail over time, even as mall vacancies inch upwards. Malls are, after all, not simply places to purchase goods. Rather, they offer a platform for services, a public space for human interaction and a centre for the community.

The amenity premium for schools is only significantly different from zero in 2019. This follows an uptick from around 2013, when MOE announced that it would guarantee ≥ 40 spaces in each school for students without prior affiliation.[24] Therefore, conditional on staying within 2km of the school, the probability of entering a top primary school rose, increasing the expected utility of the flat and consequently, the housing premium.

[24] Parents/siblings having ties to the school or a clan association affiliated with the school.

Table 3: Baseline regression estimates for each year in 2000-2019

Year	(2000)	(2001)	(2002)	(2003)	(2004)	(2005)	(2006)	(2007)	(2008)	(2009)
Distance to Nearest MRT	-0.046***	-0.049***	-0.044***	-0.043***	-0.043***	-0.041***	-0.055***	-0.064***	-0.070***	-0.061***
	(0.011)	(0.013)	(0.016)	(0.015)	(0.014)	(0.012)	(0.014)	(0.013)	(0.014)	(0.011)
Distance to Nearest Mall	-0.021**	-0.029**	-0.039***	-0.039***	-0.036***	-0.038***	-0.037***	-0.042***	-0.034***	-0.031***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.007)	(0.006)	(0.008)	(0.009)	(0.009)	(0.008)
Distance to Nearest Park	0.004	0.005	0.003	0.008	0.001	-0.000	0.001	0.003	0.006	0.006
	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)	(0.014)	(0.012)
Distance to Nearest CC	-0.003	0.004	0.002	0.007	0.008	0.006	0.005	0.012	0.010	0.007
	(0.005)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)	(0.008)
Top Pri Sch within 2km	0.004	0.002	0.015	0.003	0.011	-0.002	-0.005	0.001	0.002	-0.006
	(0.017)	(0.017)	(0.021)	(0.022)	(0.019)	(0.013)	(0.019)	(0.032)	(0.030)	(0.025)
Duration to Orchard	-0.114***	-0.097*	-0.162***	-0.172***	-0.145***	-0.165***	-0.206***	-0.226***	-0.225***	-0.208***
	(0.033)	(0.055)	(0.057)	(0.060)	(0.043)	(0.042)	(0.047)	(0.052)	(0.063)	(0.051)
Intercept	-3.607***	-3.915***	-3.313***	-2.314***	-1.621***	-1.454***	-1.293***	-1.200***	-0.783*	-0.459
	(0.271)	(0.398)	(0.390)	(0.422)	(0.340)	(0.337)	(0.343)	(0.368)	(0.442)	(0.368)
Observations	34,862	38,055	36,098	29,003	29,112	30,045	27,427	26,982	27,262	30,482
R^2	0.947	0.942	0.931	0.895	0.846	0.853	0.886	0.842	0.833	0.859
Adjusted R^2	0.947	0.942	0.931	0.895	0.845	0.853	0.886	0.842	0.833	0.859

Year	(2010)	(2011)	(2012)	(2013)	(2014)	(2015)	(2016)	(2017)	(2018)	(2019)
Distance to Nearest MRT	-0.067***	-0.062***	-0.059***	-0.064***	-0.066***	-0.054***	-0.053***	-0.064***	-0.067***	-0.057***
	(0.010)	(0.009)	(0.008)	(0.009)	(0.009)	(0.011)	(0.012)	(0.014)	(0.016)	(0.014)
Distance to Nearest Mall	-0.030***	-0.025***	-0.020***	-0.022**	-0.023**	-0.031***	-0.035***	-0.039***	-0.042***	-0.040***
	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.009)	(0.012)
Distance to Nearest Park	0.001	0.000	-0.004	-0.010	-0.005	-0.004	-0.012	-0.017	-0.018	-0.025*
	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)	(0.013)	(0.012)	(0.014)	(0.014)	(0.014)
Distance to Nearest CC	0.007	0.007	0.001	0.002	-0.004	-0.003	-0.002	0.004	0.009	0.016
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)	(0.010)	(0.012)	(0.011)	(0.011)
Top Pri Sch within 2km	-0.005	-0.006	-0.009	-0.002	0.003	0.008	0.005	0.004	0.017	0.046**
	(0.025)	(0.023)	(0.020)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.021)
Duration to Orchard	-0.194***	-0.198***	-0.198***	-0.211***	-0.211***	-0.282***	-0.296***	-0.236***	-0.255***	-0.259***
	(0.038)	(0.032)	(0.034)	(0.041)	(0.038)	(0.041)	(0.049)	(0.062)	(0.072)	(0.081)
Intercept	-0.244	-0.053	0.044	0.100	0.212	0.398	0.518	-0.027	-0.057	-0.014
	(0.285)	(0.245)	(0.254)	(0.329)	(0.317)	(0.342)	(0.396)	(0.474)	(0.532)	(0.572)
Observations	34,854	22,281	23,198	16,097	16,096	17,780	19,373	20,509	21,561	22,186
R^2	0.840	0.855	0.874	0.876	0.866	0.865	0.855	0.846	0.831	0.795
Adjusted R^2	0.840	0.855	0.873	0.875	0.866	0.865	0.855	0.845	0.831	0.795

Notes: Flat characteristics and neighbourhood dummies omitted in table. Clustered robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

5.2 Effects of Mall Openings

FIGURE 3 presents the housing price gradients before and after a mall (re)opening. While the price gradient is fairly flat before the opening of a new mall, the post-opening prices are much higher within the 800m-region. This suggests that a new mall opening may have a positive effect on housing prices, but only within the catchment area, after which the effect attenuates ("distance decay"). Prices are also lower outside the catchment area after the mall opens, possibly because they become relatively less attractive.

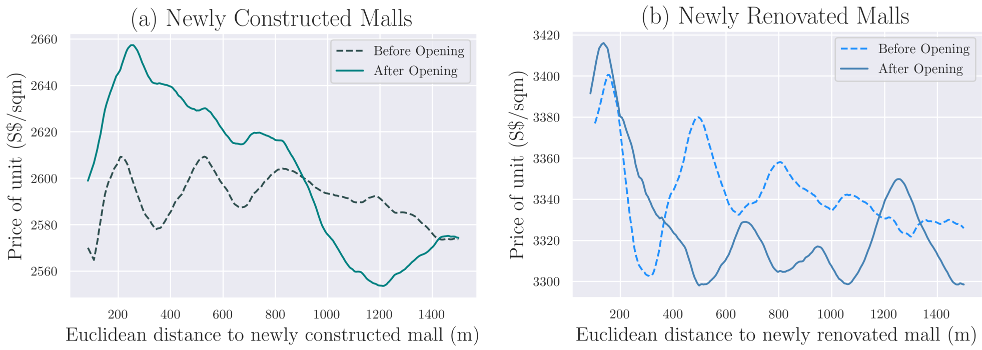


FIGURE 3: HOUSING PRICE GRADIENTS (DISTANCE)

Similar observations can be made for newly renovated malls. There is a smaller catchment area—350m radius, possibly because renovations have a weaker and less widespread effect than completely new malls.

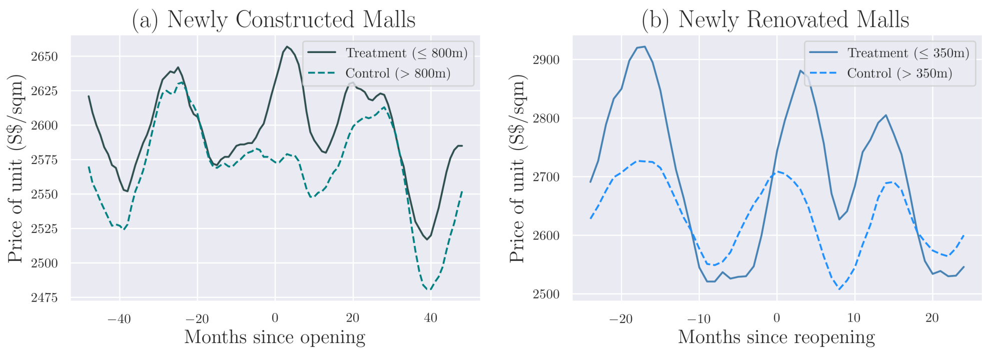


FIGURE 4: HOUSING PRICE GRADIENTS (MONTHS SINCE (RE)OPENING)

FIGURE 4 graphs prices against sale time relative to the mall's opening month, characterising the temporal dynamics of effects from mall (re)openings. FIGURE 4(a) shows that the prices of flats in the treatment and control group fluctuate similarly, but with variations in amplitude. Specifically, the gap in prices between the treatment and control groups increase about 3-4 years before the mall is scheduled to open, roughly when the projects are announced. This suggests "anticipatory effects" which Diao et al. (2017) also report for MRT network construction. There is another spike around the time the mall opens and this suggests that although anticipatory effects are present, the value of staying close to the mall has not been sufficiently priced in at the point of announcement. This is not unexpected since the amenities a mall provides may not be sufficiently priced in until there is something tangible homeowners can see and experience.

Similar observations—anticipatory effects and a further spike around opening month—can be made for the sample with newly renovated malls (FIGURE 4(b)). The slight difference is the minor dip in prices in the treatment group vis-à-vis the control group around a year before opening, roughly when renovation works are ongoing. Hence, any anticipatory effect is likely to be dampened by the temporary effect of reduced accessibility to amenities. Such an effect is not seen for newly constructed malls because there is no temporary loss in accessibility to amenities.

Using $D_c = 800$ and $D_r = 350$, I estimate the DID regressions (TABLES 4, 5).

TABLE 4: DID ESTIMATES FOR NEWLY CONSTRUCTED MALLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Study Boundary	1.5km	1.5km	1.5km	1.5km	1.5km	1.0km	2.0km
Post Opening	-0.009	-0.030	-0.033**	-0.029*	0.012	-0.003	0.006
	(0.021)	(0.018)	(0.015)	(0.017)	(0.011)	(0.014)	(0.011)
Within 800m of Mall	0.058	0.016	0.026	0.029*	0.033**	0.007	0.039***
	(0.036)	(0.018)	(0.019)	(0.016)	(0.016)	(0.018)	(0.014)
Within 800m of Mall	0.033	0.056**	0.055***	0.039***	0.037***	0.037***	0.044***
× Post Opening	(0.031)	(0.023)	(0.015)	(0.014)	(0.013)	(0.013)	(0.010)
Intercept	12.930***	9.539***	11.159***	11.544***	11.263***	11.663***	10.881***
	(0.033)	(0.183)	(0.187)	(0.807)	(0.728)	(0.925)	(0.438)
Flat Characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
N'hood Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	41,007	41,007	41,007	41,007	41,007	20,291	61,472
R^2	0.016	0.674	0.757	0.798	0.836	0.848	0.835
Adjusted R^2	0.016	0.674	0.757	0.798	0.836	0.848	0.835

Notes: Controls omitted in table. Clustered robust s.e. in parentheses. *p<0.1; **p<0.05; ***p<0.01

For both, Model (1) estimates a simple baseline model with the two dummies (*Post*, *Treat*) and their interaction variable. (2) controls for flat characteristics, (3) introduces amenity measures, (4) introduces spatial fixed effects and (5) introduces time fixed effects. (6) and (7) are robustness checks (Section 6.1.2).

While *Post* yields significantly negative estimates in 2 models for newly constructed malls (TABLE 4), it yields a positive estimate that is not significantly different from zero

Table 5: DID estimates for newly renovated malls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Study Boundary	1.5km	1.5km	1.5km	1.5km	1.5km	1.0km	2.0km
Post Opening	-0.006	-0.002	-0.001	0.015	-0.018*	-0.015	-0.008
	(0.014)	(0.022)	(0.022)	(0.020)	(0.011)	(0.012)	(0.009)
Within 350m of Mall	0.117***	0.152	0.064**	0.069***	0.075***	0.058***	0.084***
	(0.045)	(0.101)	(0.025)	(0.015)	(0.018)	(0.019)	(0.026)
Within 350m of Mall	0.013	-0.007	0.008	-0.008	-0.009	-0.001	-0.016***
× Post Opening	(0.032)	(0.016)	(0.021)	(0.013)	(0.007)	(0.008)	(0.005)
Intercept	12.960***	9.789***	10.701***	12.616***	12.107***	8.876***	11.841***
	(0.080)	(0.431)	(1.697)	(0.922)	(0.870)	(0.676)	(0.872)
Flat Characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Amenities	No	No	Yes	Yes	Yes	Yes	Yes
N'hood Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	14,932	14,932	14,932	14,932	14,932	7,868	19,580
R^2	0.006	0.668	0.692	0.882	0.890	0.921	0.877
Adjusted R^2	0.005	0.668	0.692	0.882	0.890	0.921	0.876

Notes: Controls omitted in table. Clustered robust s.e. in parentheses. *p<0.1; **p<0.05; ***p<0.01

after controlling for time fixed effects. Hence, the negative estimates are likely capturing unobserved time fixed effects and there is no change in the amenity premium post-opening for the control group.

The estimated coefficients of the interaction variable suggest differential effects inside and outside the catchment area post-opening, as noted by the graphical evidence. These estimates are significantly positive, even after adding in controls. The significantly positive estimates of the coefficient for $Treat$ alone points to potential anticipatory effects for flats lying within the catchment area.

Such anticipatory effects are also reflected in the estimates of the coefficient of $Treat$ for newly renovated malls (Table 5). The point estimates for coefficients of $Treat$ are higher for newly renovated malls than for newly constructed malls but this is expected because the catchment area is smaller and therefore the average effect is more intense.

The estimated coefficient of the interaction variable in (5) is negative and insignificant, suggesting that differential post-reopening effects between the treatment and control groups shown in the graphical evidence may have been reflecting other determinants of housing prices.

Post alone yields imprecise estimates except in (5) where the estimate is significantly negative (at 10% level). This suggests that the true value of quality improvement in amenities is lower than the expected value, thereby leading to a minor correction in prices in both treatment and control groups post-reopening.

6 Robustness and Heterogeneity

6.1 Robustness

6.1.1 Baseline

I took several liberties in the baseline estimation:

TABLE 6: POSSIBLE OPTIONS FOR ESTIMATION

Deflator	**GDP per capita**, GDP deflator, Resale Price Index
City Centre	**CRD**, CBD
Accessibility (Amenities)	**Distance**, Duration
Accessibility (City Centre)	Distance, **Duration**
λ	**Common $\boldsymbol{\lambda}$**, Different λ before and after 2010

Notes: Choices opted in Section 4.1 are **bolded**.

To check for robustness, I estimate all 48 permutations but the overall conclusions are unchanged.[25] After all, the alternative variables are highly correlated with the baseline variables and are unlikely to yield very different results.

Using travel duration as *the* proximity measure may be of particular interest given reports of increased efficiency (Lu et al., 2014; Cao et al., 2019). FIGURE 5 shows that the signs and trends of estimated coefficients remain unchanged, suggesting that the results are robust to the choice of proximity measure.[26] While Cao et al. (2019) report higher adjusted-R^2 when using duration-based measures, FIGURE 5 suggests that duration-based measures generally yield noisier estimates. In fact, the adjusted-R^2s are lower than in the baseline across 2000-2019. Cao et al. (2019) find improved performance because they conduct the study at lower spatial resolution, sacrificing heterogeneity to reduce noise. At higher spatial resolution, duration-based measures are likely to be noisier than ED, and poorer performance is expected.

6.1.2 Effects of Mall Openings

While choosing 1.5km as the study area's radius is informed by data, the choice of radius affects the control group's size and therefore, the estimated amenity premium. Too large

[25] Due to space limitations, results are omitted. Tables are available on request.

[26] School dummy is omitted since it is distance-based.

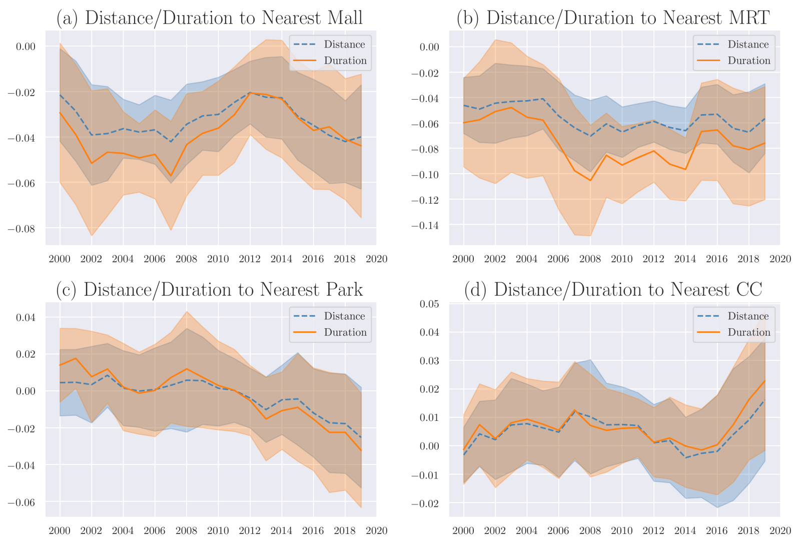


Figure 5: Robustness Check: Coefficients of Amenity Measures

a radius will include in the control group flats that are less comparable to the treatment group due to unobserved heterogeneity, confounding the results.

I check for robustness by testing radii of 1km and 2km. These are reported in columns (6) and (7) of Tables 4 and 5. For both newly constructed and renovated malls, the amenity premium for staying in the catchment area is stronger when the control group includes flats further away from the mall of interest (2km radius) and weaker when it only includes flats closer to the mall (1km radius). For newly constructed malls, the DID estimate also increases when the study area expands to 2km radius. Crucially, the signs of these effects are unchanged, pointing to general robustness. Furthermore, how the magnitude of estimates change reflects the empirical regularity of distance decay, reinforcing the overall claim that flats closer to the mall incur a higher amenity premium.

6.2 Heterogeneity in MRT Quality

Barring Section 4.2 where the effects of mall renovations are tested, I assume homogeneity in amenities when using proximity to the nearest amenity to measure accessibility to amenities. While it is difficult to produce data to quantify heterogeneity, I explore one aspect of heterogeneity in MRT stations—some stations are aboveground (noise-generating) while others are underground (noise-isolating). By interacting a dummy of whether the station is aboveground with the amenity measure for MRT, I estimate separate effects.

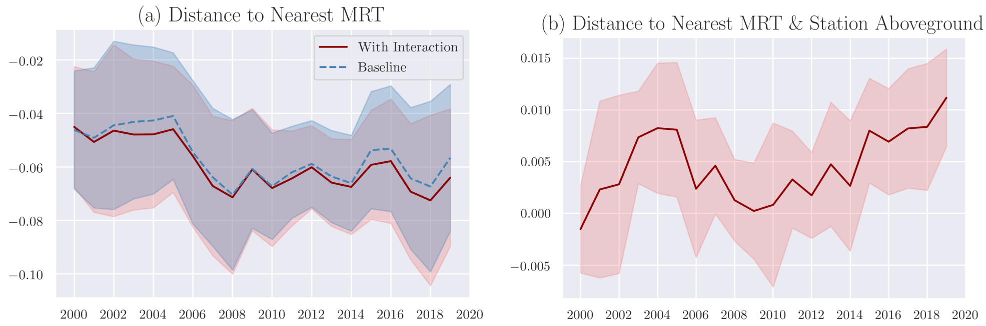


Figure 6: Coefficients for MRT measure and interaction term

Figure 6(a) shows that the point estimates for the MRT measure are lower than in the baseline, which suggests a higher premium placed on staying close to trains that run underground. Figure 6(b) shows that the coefficient on the interacted variable is positive, suggesting that noise from trains running aboveground yields a negative externality. Barring the plunge around 2008, the coefficient (negative premium) has increased over time and is statistically significant since 2015. This may have resulted from a rise in the proportion of stations built underground, increasing the relative disamenity of staying close to an aboveground station.

6.3 Heterogeneity in Demographics

Population demographics are likely to affect the amenity premia. Specifically, we may be concerned with age because lifestyle habits, needs and lived experiences vary across ages, affecting preferences over amenities. To gauge how older residents differ from younger residents, I construct a demographic dummy based on each neighbourhood's population distribution. Using population demographic data, I rank the 55 neighbourhoods by the proportion of elderly dependents[27] for each year in the sample and separate the dataset into two—flats in the top-27 neighbourhoods in the year of purchase and flats in the bottom-half.

By running a separate regression for the top half ("older areas") and the bottom half ("younger areas"), I estimate two sets of coefficients. I graph the coefficients against time and superimpose estimates from the two samples on the same graph (Figure 7).

[27] Age ≥ 65

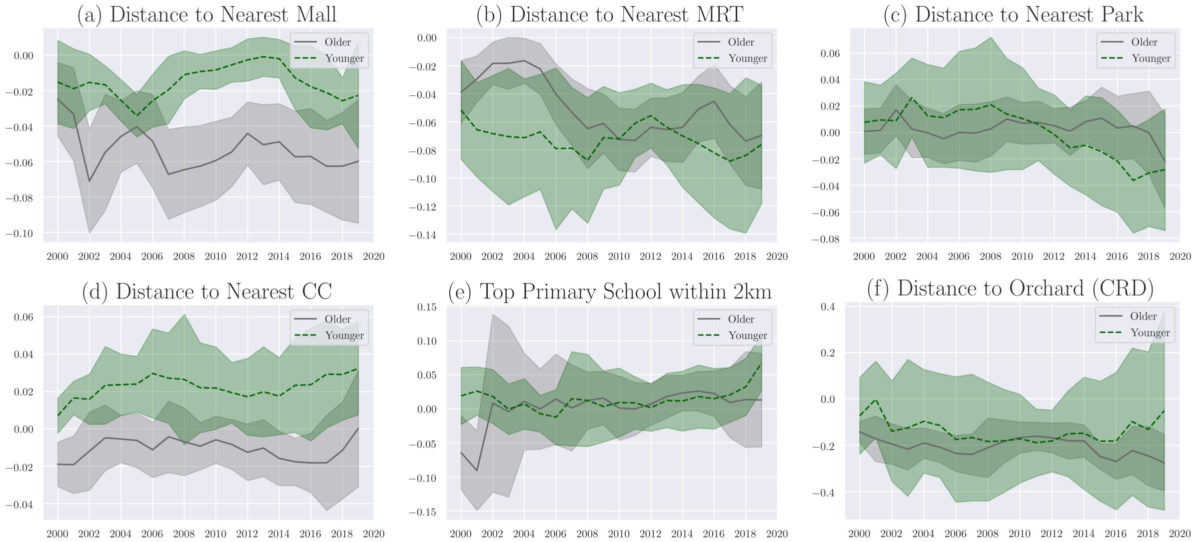


FIGURE 7: EFFECTS OF DEMOGRAPHICS ON COEFFICIENTS OF AMENITY MEASURES

There are two interesting trends. Firstly, residents from older areas place a stronger positive premium on accessibility to retail. FIGURE 7(a) shows that the point estimates of the coefficients in older areas are consistently lower than those in the younger areas with little overlap in the confidence intervals.[28] The point estimates for CRD are also generally lower in older areas (FIGURE 7(f)), suggesting stronger preference for retail in older areas. Of course, the CRD estimate also captures accessibility to CBD but since this is likely to matter less in older areas, the differential premium placed on retail in older and younger areas is likely more pronounced. Intuitively, older residents may have more recreation time and may prefer shopping in brick-and-mortar stores to shopping online. Conversely, residents from younger areas place a stronger positive premium on accessibility to transport (FIGURE 7(b)), likely because a larger proportion work, and value accessibility to the MRT network.[29]

[28]The estimated coefficients in older areas are found to be statistically different from those in younger areas for 15/20 years.

[29]There is more noise in the estimated coefficients for CRD and MRT in younger areas. Hence, the estimated coefficients in older areas are statistically different from those in younger areas for 1/20 and 5/20 years respectively.

7 Conclusions

This paper extends the "Consumer City" literature by studying how the amenity premia for different amenities have evolved over the last two decades using a case study that circumvents endogeneity issues, with an extensive self-constructed dataset. The results capture a strong amenity premium for accessibility to retail (malls and CRD) and transport (MRT), as measured by Singapore housing prices. Crucially, there is no downward trend in the amenity premia within the sample period (2000-2019) despite advances in technology that have provided greater ease in shopping from home. Running the regressions on two samples—one comprising areas with an older demographic and the other a younger demographic—suggests heterogeneous preferences for amenities. Specifically, there is a stronger premium placed on accessibility to retail in older areas and a stronger premium placed on accessibility to MRT in younger areas.

As the first paper to study mall openings (and reopenings) in Singapore in a quasi-experimental setting, I show that there are anticipatory effects for both mall construction and renovation. These effects generate an amenity premium within a sufficiently close neighbourhood of the mall (catchment area) and exhibit distance decay. While the premium for flats within the catchment area rises further when a new mall opens, it does not when a renovated mall reopens. Still, it remains that homeowners place significant value on the accessibility and quality of malls in the vicinity of their homes.

Despite the dataset's extensiveness, the paper assumes homogeneity in the quality of amenities. As reflected in the extension on MRT stations, aboveground and underground stations are valued differently. While the assumption of homogeneity of shopping malls is fairly innocuous, more extensive data collection may provide further insights.

While the pandemic has accelerated the demise of many brick-and-mortar stores both in Singapore and around the world, the premium placed on accessibility to malls has been strong and may have even increased towards the end of the sample period (2019). Urban planners and property developers need to pay more attention to the importance of consumption amenities in cities. Retail space is valued by residents not simply for its accessibility to goods but also to services and as a space itself. The higher premium placed on accessibility to malls in older areas, combined with an ageing population, reinforces the importance of leveraging retail space to improve social welfare. Online-to-offline retail concepts, the incorporation of more activity-based tenants, and the synthesis of work and play in retail space, among other creative concepts, are perhaps steps in the right direction to ensure that the "Consumer City" remains as attractive as ever.

References

Agarwal, S., Rengarajan, S., Sing, T. F. and Yang, Y. (2016), 'School allocation rules and housing prices: A quasi-experiment with school relocation events in Singapore', *Regional Science and Urban Economics* **58**, 42–56.
URL: *https://www.sciencedirect.com/science/article/abs/pii/S0166046216000089*

Anderson, S. and West, S. (2006), 'Open space, residential property values, and spatial context', *Regional Science and Urban Economics* **36**(6), 773–789.
URL: *https://EconPapers.repec.org/RePEc:eee:regeco:v:36:y:2006:i:6:p:773-789*

Blomquist, G. C., Berger, M. C. and Hoehn, J. P. (1988), 'New estimates of quality of life in urban areas', *American Economic Review* **78**(1), 89–107.
URL: *https://EconPapers.repec.org/RePEc:aea:aecrev:v:78:y:1988:i:1:p:89-107*

Brueckner, J. K., Thisse, J.-F. and Zenou, Y. (1999), 'Why is central Paris rich and downtown Detroit poor?: An amenity-based theory', *European Economic Review* **43**(1), 91–107.
URL: *https://ideas.repec.org/a/eee/eecrev/v43y1999i1p91-107.html*

Cao, K., Diao, M. and Wu, B. (2019), 'A big data–based geographically weighted regression model for public housing prices: A case study in Singapore', *Annals of the Association of American Geographers* **109**(1), 1–14.
URL: *https://ink.library.smu.edu.sg/sis_research/5460/*

Carlino, G. A. and Saiz, A. (2019), 'Beautiful city: Leisure amenities and urban growth', *Journal of Regional Science* **59**(3), 369–408.
URL: *https://ideas.repec.org/a/bla/jregsc/v59y2019i3p369-408.html*

Davies, K. (2012), 'The composition of Singaporean shopping centres', *The International Review of Retail, Distribution and Consumer Research* **22**(3), 261–275.
URL: *https://doi.org/10.1080/09593969.2012.682600*

Diao, M., Fan, Y. and Sing, T. F. (2017), 'A new Mass Rapid Transit (MRT) line construction and housing wealth: Evidence from the Circle Line', *Journal of Infrastructure, Policy and Development* **1**(1), 64–89.
URL: *https://systems.enpress-publisher.com/index.php/jipd/article/view/22*

Gabriel, S. and Rosenthal, S. (2004), 'Quality of the business environment versus quality of life: Do firms and households like the same cities?', *The Review of Economics and Statistics* **86**(1), 438–444.
URL: *https://EconPapers.repec.org/RePEc:tpr:restat:v:86:y:2004:i:1:p:438-444*

Gibbons, S., Mourato, S. and Resende, G. (2014), 'The amenity value of English nature: A hedonic price approach', *Environmental and Resource Economics* **57**, 175–196.
URL: *https://link.springer.com/article/10.1007/s10640-013-9664-9*

Glaeser, E. L. (2007), The economics approach to cities, Working Paper 13696, National Bureau of Economic Research.
URL: *http://www.nber.org/papers/w13696*

Glaeser, E. L. (2008), *Cities, Agglomeration, and Spatial Equilibrium*, Oxford University Press.
URL: *https://EconPapers.repec.org/RePEc:oxp:obooks:9780199290444*

Glaeser, E. L., Kolko, J. and Saiz, A. (2001), 'Consumer city', *Journal of Economic Geography* **1**(1), 27–50.
URL: *https://EconPapers.repec.org/RePEc:oup:jecgeo:v:1:y:2001:i:1:p:27-50*

Google Maps Platform (n.d.), 'Distance Matrix API'.

Gyourko, J. and Tracy, J. (1991), 'The structure of local public finance and the quality of life', *Journal of Political Economy* **99**(4), 774–806.
URL: *https://EconPapers.repec.org/RePEc:ucp:jpolec:v:99:y:1991:i:4:p:774-806*

Hoehn, J. P., Berger, M. C. and Blomquist, G. C. (1987), 'A hedonic model of interregional wages, rents, and amenity values', *Journal of Regional Science* **27**(4), 605–620.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9787.1987.tb01184.x*

Housing and Development Board (2020), 'Estimated Singapore resident population in HDB flats'.
URL: *https://data.gov.sg/dataset/estimated-resident-population-living-in-hdb-flats?resource_id=a7d9516f-b193-4f9b-8bbf-9c85a4c9b61b*

Housing and Development Board (2021), 'Resale flat prices'.
URL: *https://data.gov.sg/dataset/resale-flat-prices?resource_id=adbbddd3-30e2-445f-a123-29bee150a6fe*

Jacobs, J. (1961), *The death and life of great American cities*, Random House, New York.

Jang, M. and Kang, C.-D. (2015), 'Retail accessibility and proximity effects on housing prices in Seoul, Korea: A retail type and housing submarket approach', *Habitat International* **49**, 516–528.
URL: *https://www.sciencedirect.com/science/article/pii/S0197397515001393*

J.P. Morgan (2019), ‘2019 global payments trends report - Singapore country insights’, *2019 Global Payments Trends* .
URL:
https://www.jpmorgan.com/europe/merchant-services/insights/reports/singapore

Lloyd, R. and Clark, T. N. (2001), The city as an entertainment machine, *in* K. F. Gotham, ed., ‘Critical Perspectives on Urban Redevelopment’, Emerald Group Publishing Limited, Bingley, pp. 357–378.

Lu, B., Charlton, M., Harris, P. and Fotheringham, A. S. (2014), ‘Geographically weighted regression with a non-Euclidean distance metric: a case study using hedonic house price data’, *International Journal of Geographical Information Science* **28**(4), 660–681.
URL: *https://doi.org/10.1080/13658816.2013.865739*

Marshall, A. (1890), *The Principles of Economics*, McMaster University Archive for the History of Economic Thought.
URL: *https://EconPapers.repec.org/RePEc:hay:hetboo:marshall1890*

National Parks Board (2020), ‘NParks parks’.
URL: *https://data.gov.sg/dataset/nparks-parks*

National University of Singapore (2021), ‘Historical maps of Singapore’.
URL: *https://libmaps.nus.edu.sg/*

Remember Singapore (2013), ‘60 years of community centres’.
URL: *https://remembersingapore.org/2013/03/24/history-of-community-centres/*

Roback, J. (1982), ‘Wages, rents, and the quality of life’, *Journal of Political Economy* **90**(6), 1257–78.
URL: *https://EconPapers.repec.org/RePEc:ucp:jpolec:v:90:y:1982:i:6:p:1257-78*

Rosen, S. (1974), ‘Hedonic prices and implicit markets: Product differentiation in pure competition’, *Journal of Political Economy* **82**(1), 34–55.
URL: *https://EconPapers.repec.org/RePEc:ucp:jpolec:v:82:y:1974:i:1:p:34-55*

Rosen, S. (1979), Wages-based indexes of urban quality of life, *in* P. Mieszkowski and M. Straszheim, eds, ‘Current Issues in Urban Economics’, Johns Hopkins University Press, pp. 74–104.

SG Schooling (2021), ‘P1 ballot history’.
URL: *https://sgschooling.com/*

Shahid, R., Bertazzon, S., Knudtson, M. L. and Ghali, W. A. (2009), 'Comparison of distance measures in spatial analytical modeling for health service planning', *BMC Health Services Research* **9**(1), 1–14.
URL: *https://doi.org/10.1186/1472-6963-9-200*

Singapore Department of Statistics (2001), 'Census of population 2000: Advance data release'.
URL: *https://www.singstat.gov.sg/publications/cop2000/cop2000adr*

Singapore Department of Statistics (2011), 'Singapore census of population 2010, statistical release 3: Geographic, distribution and transport'.
URL: *https://www.singstat.gov.sg/publications/cop2010/census10_stat_release3*

Singapore Department of Statistics (2016), 'General Household Survey (GHS) 2015'.
URL: *https://www.singstat.gov.sg/publications/ghs/ghs2015content*

Singapore Department of Statistics (2020), 'Population trends'.
URL: *https://www.singstat.gov.sg/publications/population/population-trends*

Singapore Department of Statistics (2021), 'National accounts'.
URL: *https://www.singstat.gov.sg/find-data/search-by-theme/economy/national-accounts/latest-data*

Singapore Land Authority (n.d.), 'OneMap API'.

Song, Y. and Sohn, J. (2007), 'Valuing spatial accessibility to retailing: A case study of the single family housing market in Hillsboro, Oregon', *Journal of Retailing and Consumer Services* **14**(4), 279–288.
URL: *https://www.sciencedirect.com/science/article/pii/S0969698906000488*

Urban Redevelopment Authority (2019), 'Master plan written statement 2019'.
URL: *https://www.ura.gov.sg/-/media/Corporate/Planning/Master-Plan/MP19writtenstatement.pdf?la=en*

Woo, J. (2018), 'Food fight! the battle for the food delivery market', *The Business Times* .
URL: *https://www.businesstimes.com.sg/brunch/food-fight-the-battle-for-the-food-delivery-market*

Yoon, E. (2019), 'Netflix will keep growing because none of us can stop watching screens', *Barron's* .
URL: *https://www.barrons.com/articles/netflix-will-keep-growing-because-none-of-us-can-stop-watching-screens-51548950332*

Zhang, L., Zhou, J., Hui, E. and Wen, H. (2019), 'The effects of a shopping mall on housing prices: A case study in Hangzhou', *International Journal of Strategic Property Management* **23**, 65–80.
URL: *https://doi.org/10.3846/ijspm.2019.6360*