Gentrification in the Global East?: Analysis of the Impacts of Built Heritage on Residential Property Value in Singapore's Gentrified Neighbourhoods

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Abstract

Built heritage conservation, and attendant restoration of historic buildings and structures possessing architectural, historical and artistic values, has received growing scholarly attention as a source of neighbourhood gentrification across global cities. While traditional and archaic landscapes were once perceived as hindrances to the ascent of global cities, it is now enlisted within the toolkit of urban policy-making amidst inter-city competition for investment and skilled workers, gaining increasing traction in the Global East. Yet, deficient systematic analyses of neighbourhood change in the latter clouds an understanding of how dominant understandings of gentrification in the Global North must be expanded to encapsulate multiple and diverse manifestations of gentrification in the Global East.

In Singapore, while numerous authors adopt the language of gentrification to describe emerging changes in the residential property market, and economic and demographic make-up of residents arising from state-sponsored restoration of vernacular, historic structures, studies are sparse in offering coherent assessment of such neighbourhood transition to quantify the impacts of gentrification. Therefore, this paper aims to illuminate a typology of pathways of neighbourhood transition from 2000 to 2015 in Singapore, and to quantify the value of built heritage within the residential property market in gentrified neighbourhoods. By drawing attention to the amenity accorded to cultural heritage despite the potential costs of heritage-induced gentrification, it hopes to inspire much more targeted and measured policy-making.

To achieve these objectives, the paper uses a combination of clustering algorithms to achieve a classification of neighbourhoods and neighbourhood change sequences as well as spatial hedonic regressions on resale flat transactions in gentrified neighbourhoods to examine the impact of proximity to heritage on flat prices. It finds gentrified neighbourhoods concentrated towards city-centre, forming concentric rings around the commercial core. Proximity to heritage was consistently significant across all regression models, with some evidence of distance-decay.

Declaration of Authorship

I, Jamie Ser Nee Tan, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. This dissertation is 11,984 words in length.

Signed: ______________________

Date: 24 August 2020

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Acronyms and Abbreviations

API	Application Programming Interface
CBD	Central Business District
CLC	Centre for Liveable Cities, Singapore
HDB	Housing Development Board of Singapore
MAUP	Modifiable Areal Unit Problem
OLS	Ordinary Least Squares
PAM	Partitioning Around Medoids
PCA	Principal Component Analysis
SEM	Spatial Error Model
SLM	Spatial Lag Model
URA	Urban Redevelopment Authority of Singapore
UK	United Kingdom
US	United States

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1. Introduction

The conservation of cultural and architectural heritage has received considerable attention in academic literature on Western cities in the Global North (Zukin, 1987; Miles and Paddison, 2005), where culture-led regeneration has become synonymous with gentrification and middle-class dominance in neighbourhoods experiencing historic preservation (Rosseau, 2009), in tune with an increasingly hegemonic urban policy discourse celebrating the commodification of heritage in city rebranding and bolstering international competitiveness of the entrepreneurial city (Harvey, 1989). By comparison, this subject has received scant attention in the Global East, although East Asian cities have been increasingly confronted with the conservation-development dilemma (Kong and Yeoh, 1994). However, despite the threat of modernisation and urbanisation, perception of East Asia's rich built heritage not merely as palimpsests of the past, but as income-generating urban assets have gained ground among urban policymakers (Yuen, 2005).

Singapore, a nascent city-state which underwent widespread demolition of vernacular structures in its early years of independence, now with yet over 100ha of land dedicated to historic preservation (Yuen and Hock, 2001) exemplifies this gentrification-heritage nexus where gazetting of traditional architecture in particular neighbourhoods has been accompanied by subtle, incremental alterations in their social and demographic character (Hu and Caballero, 2016). Thus, while 'gentrification' has not been a term widely formalised in policy discourses, traces of it in Singapore identified in qualitative studies by numerous scholars (Chang, 2016; Wong, 2005; Pow, 2009) suggest need for a systematic examination of neighbourhood change over time, while warranting better understanding of the value of built heritage, in at least economistic terms captured through quantitative studies (Tan and Ti, 2020).

Therefore, this paper aims to critically examine typologies of neighbourhood change in order to provide insight into different pathways of neighbourhood transition in Singapore, while constructing an effective visualisation of Singapore's gentrification landscape to aid spatial targeting of policy-making. Second, in response to paucity of work in this area within Singapore, it seeks to contribute to the formative body of work on the variegated permutations of gentrification processes in the global East, and build on current understandings of theoretical continuities and incongruencies of Singapore's unfolding neighbourhood change with hegemonic narratives based on experiences of the Global North. Finally, it seeks to capitalise on the rich dataset of public resale housing transactions so as to provide insight into the value placed by Singaporean homeowners on heritage goods in gentrified neighbourhoods, vis-à-vis other structural and locational attributes contributing to property values.

Singapore constitutes an interesting study site for exploring gentrification in an East Asian context for several reasons. First, pragmatist state attitudes towards cultural and built heritage (Saunders, 2004) arguably engender residential and commercial gentrification pressures. The preservation and enhancement of building facades in Singapore is often accompanied by selective new uses and residents defined by the state, as part of Singapore's drive towards achieving a distinctive brand and city identity (Yuen and Hock, 2001; Kong and Yeoh, 1994). Thus, heritage conservation has been a key agent of neighbourhood change in Singapore (Hu and Caballero, 2016). Secondly, from the lens of comparative urbanism (Robinson, 2011), locating the analysis within Singapore responds to Waley's (2016:620) calls to "[provincialise] the script emanating from the Global North by shrinking it so that it fits within a busier conceptual space…[and to] seek a balance between the general and the particular". By comparing gentrification's socio-spatial manifestations in Singapore with existing narratives, it hopes to destabilise Northern conceptions of neighbourhood change.

Therefore, the key research question of this paper is: *How might longitudinal census data and resale prices of residential properties lend insight into spatial patterns of potential neighbourhood gentrification prompted by conserved built heritage in Singapore?* This will be answered by decomposing it into several sub-questions. Firstly, where might neighbourhood gentrification be happening in Singapore? Secondly, within gentrified areas, to what extent does heritage confer a premium on house prices? It should be caveated these questions are not attempting to prove heritage designation boosts resale values of flats *over time*, insomuch as it seeks to uncover the value of heritage in gentrified neighbourhoods.

Ultimately, amidst heightened academic criticism against gentrification and how it has potentially wrought destruction on the traditional character and spirit of older neighbourhoods in Singapore, this paper seeks to create a more tempered middle-ground enhancing the evidence base not only for socio-economic polarisation to potentially accrue through gentrification, but also the prospective economic benefits arising from heritage conservation. It also draws attention to gentrifying neighbourhoods where there is exigent need to manage potential neighbourhood-level socio-economic divisions with targeted policies, demonstrating need for urban renewal policies to navigate these pushbacks cautiously without undermining the value of conserving built heritage.

Indeed, the former should not negate the potential for the benefits of heritage conservation to far surpass their economic and social costs under proper policy execution (Ruijgrok, 2006). Amidst continued needs for land optimisation due to space constraints in the small city-state, state-endorsed heritage conservation may not be a foregone conclusion (Yeoh and Huang, 1996). Rather, as population expansion in Singapore continues, while more diverse land use requirements emerge in these uncertain times, there is no guarantee built heritage will be left untouched in the absence of stronger policy and academic support.

This paper begins with a critical overview of existing work on the role of heritage in prompting neighbourhood gentrification and how such processes manifest themselves through demographic change and in the housing market. Through PAM clustering and sequence analysis, it identifies Singaporean neighbourhoods that are characteristic of gentrified areas. Ordinary-Least-Squares and spatial regression models are run on resale flat transactions limited to those within gentrified areas. Key findings regarding neighbourhood change typologies, spatiality of Singapore's gentrification and impacts of heritage on resale flats in gentrified areas are presented in the results section. The discussion section expands on wider theoretical and policy implications, while contextualising these results to Singapore. The conclusion summarises key contributions, while highlighting future recommendations for research.

2. Literature Review

This section combines existing literature on the relationship between conserved built heritage and gentrification, and empirical effects of heritage preservation on property values and socio-economic, demographic character of neighbourhoods by locating these processes both generally in the Global North, East and specifically in Singapore. It critically overviews existing approaches employed to a) map trajectories of neighbourhood gentrification and b) estimate price effects of heritage on properties in gentrifying neighbourhoods, concluding with existing gaps in knowledge the paper seeks to address.

2.1. The Role of Built Heritage Conservation in Gentrifying Neighbourhoods

The term 'gentrification' was initially coined by British-German sociologist Ruth Glass in 1964 to encapsulate neighbourhood changes materialising in inner-city of London where emergence of an affluent British 'gentry' and subsequent displacement of working-class residents altered the socio-economic character of affected neighbourhoods (Glass, 1964). In recent years, this phenomenon has transcended urban cores of cities in the Global North, penetrating cities lower on the urban hierarchy, rural areas and manifesting in new-build structures with several residential and commercial uses (Lees, 2003). Responding to Atkinson's (2003:2348) and Clark's (2005) calls for a more comprehensive, expansive definition of 'gentrification' to address this emerging complexity, Lees (2008:15) broadly defines gentrification as "transformation of a working-class or vacant area of the central city into middle-class residential and/or commercial use".

However, Shin et al (2016:457) stresses the particularities of gentrification in the Global East may evade such a working definition. Cities such as Singapore, Hong Kong, South Korea and Taiwan have developmentalist 'property states' wielding immense ownership of land, enabling large-scale state-sponsored urban redevelopment (Haila, 2000) and new-build gentrification, involving widespread demolition of old historic housing and replacement with luxury residential and commercial spaces, to be commonly observed (Moore, 2013). Curiously, rather than perceived as merely obstruction to modernity, historic buildings are increasingly recapitalised by Asian cities in their quest for a distinct city image, with abandoned waterfronts, factories or historic districts transformed into cultural innovations with creative uses (Yuen, 2013). Such built heritage forms encompass both historic buildings, monuments and structures imbibed with perceived architectural and aesthetic value (Stipe, 2003; Tweed and Sutherland, 2007).

To understand changing policy impetus behind the perceived role of heritage in urban redevelopment, it is necessary to make recourse to literature on urban entrepreneurialism. This roots gentrification in the post-Fordist, neoliberal era where intense competition amongst global cities to assert standing as command-and-control-centres of the global economy (Harvey, 1989; Sassen, 1991, 1995) has led city governments to be preoccupied with place-making strategies. Policy discourses on urban economic renaissance have been increasingly saturated with presumptions that the ‘creative class’, key agents of specialised services and knowledge essential to economic revitalisation (Florida, 2002), need to be lured with cultural spectacles – ‘authentic’ historical buildings, arts and music spaces and various work-and-play spaces (Peck, 2005). Such discourses augment the rising popularity of ‘culture-led regeneration’ approaches guiding the revitalisation of working-class neighbourhoods with industrial heritage into desirable, attractive, ‘hip’ environments to attract international capital and highly-skilled workers (Zukin, 1995), establishing an edge of differentiation for the city (Short, 1996).

Yet, as Mathews and Picton (2014:337) observe, historic preservation “[has repeatedly been shown] to work as precursors to gentrification, ushering in new systems of value that attract higher income residents and businesses”. Similarly, Shaw (2005) notes protection and restoration of declining structures have constituted a catalyst for gentrification. For Zukin (1987:135), such cultural architecture, while synonymous with production of economic value in the post-industrial city, often leads to two main gentrification outcomes.

> *“ In a subtle way, the ideology of historic preservation facilitates the removal of a pre-gentrification population, especially those residents whose modernization of their homes is incongruous with*

> *the spirit of authenticity in the gentrifiers' own restoration. But the pragmatic wedge of their displacement is rising rents and higher sale prices for homes in gentrifying neighbourhoods."*

While historic preservation might lead to a changing demographic and socio-economic profile of residents with prominent elite and upper middle-class occupation of central city neighbourhoods, its lucrative edge as an urban policy tool lies in escalation of real estate values.

2.2. Singapore's 'Geography of Gentrification': Gentrification Aesthetics and Neighbourhood Change

Although effects of built heritage on inflating property values and altering the socio-economic-demographic composition of neighbourhoods is both culturally and politically-determined (Henderson, 2011), which precludes linear extrapolation to other socio-political contexts (Graham et al, 2000), the critical role of heritage conservation in sparking neighbourhood change in Singapore is observed by numerous authors (Lih, 2005; Wong, 2005; Yuen, 2006; Chang, 2016).

In the 1960s and 70s, close to 70% of Singapore's colonial landscape was razed as part of the state's earlier 'slash-and-build' attempts to modernise living environments (Savage, 2001). However, the 1980s ushered in a drastic paradigm shift when the Urban Redevelopment Authority (URA) published the Conservation Master Plan, singling out historic ethnic enclaves and city centre districts housing colonial era buildings to be gazetted for conservation, including Chinatown, Little India, Kampong Glam, Singapore River and the Civic District (Sim, 1996).

However, unlike classical gentrification, gentrification prompted through heritage preservation may not be solely confined to areas within the city centre or commercial districts. As Yuen (2006:838) notes, the Master Plan 2003 sought to "retain the familiar old-world charm of familiar neighbourhoods", including vernacular residential neighbourhoods, such as older public housing estates with highly unique architectural facades (Chang, 2016) – Balestier, Tanjong Katong, Jalan Besar, and Joo Chiat/East Coast Road – bordering the fringe of the city centre, which contain traditional indigenous architectural forms such as 19th century shophouses (Yeoh, 2000).

While the term ‘gentrification’ is not deployed within Singapore’s formal planning discourse (Hu and Caballero, 2016), the Singapore Government has actively promoted adaptive and creative reuse of historical designations and old housing estates by various cultural, arts and commercial organisations (Chang, 2016) upon recognition of their income-generating potential and ability to yield commercial profit (Langston et al, 2008) and bolster Singapore’s distinctive visual identity to attract visitors (Yeoh, 2000).

Preservation of historic shophouse residences have facilitated return of upper middle-class Singaporeans and expats to designated cultural and historical neighbourhoods, setting in motion processes of neighbourhood change (Chang and Teo, 2001, 2009), who constitute part of the creative class who may be working within the vicinity. Tan (2014) highlights the creation of ‘little bohemia’ in One-North commercial area where former colonial Black and White bungalows and low-rise shophouse apartments have been repurposed into upscale residential units by younger, more well-educated expatriates and Singaporeans working within the commercial development. Such developments contribute to skyrocketing rents, potentially diminishing housing affordability (Henderson, 2011).

Contrary to policy intent to foster cultural distinctiveness and ‘community spirit’ (Yuen, 2006), widespread scholastic concerns over gentrification’s consequent displacement of lower-income households and potential conflicts between new and incumbent residents (Marcuse, 1989; Slater, 2009) have been echoed by Hu and Caballero (2016) on Singapore. They observe, in historic neighbourhoods, long-time businesses are increasingly replaced by boutique cafes, restaurants and ‘hipster’ stores patronised by a younger clientele, while elderly residents suffer from a ‘mismatch’ of services and place identities (Hu and Caballero, 2016:7).

2.3. Examining Changing Socio-Economic and Demographic Composition of Gentrified Neighbourhoods

In gentrification literature, numerous authors have adopted geodemographic classifications or typologies to cluster neighbourhoods into discrete classes based on longitudinal census data. For example, Webber (2007) uses UK's MOSAIC system of consumer profiles to establish areas of England and Wales exhibiting gentrification characteristics. Lansley et al (2019) adopt a similar approach of classification with highly granular administrative and consumer postcode-level data to focus specifically on ethnic displacement within the gentrified London neighbourhood of Spitalfields, reporting significant growth in population of young, male, White professionals with simultaneous decline in traditional Bangladeshi population groups.

Highly comprehensive studies have been undertaken by Ling and Delmelle (2016) and Delmelle (2016) who develop a typology of various trajectories of spatio-temporal neighbourhood change, including but not limited to gentrification, with longitudinal census data, by producing neighbourhood classification through k-means clustering algorithm and sequential pattern mining algorithms.

Table 1. *Summary of input variables in Ling and Delmelle (2016), Delmelle (2016)*

Input Variables
% persons with at least a 4-year degree
% unemployed
% manufacturing employees
% below poverty level
% owner-occupied
% multi-unit structures
Median home values

% structures built more than 30 years ago

Ling and Delmelle (2016) find gentrified neighbourhoods are characterised by ‘Young Urban’ clusters with highly-educated residents, highest housing values, and largest share of recent in-movers. Yet, Patias et al (2019) suggest there remains the Modifiable Areal Unit Problem where variation in geographical units of neighbourhoods results in inconsistent representations of spatial patterns. Li and Xie’s (2018) ‘prototype’ clustering approach attempts to address this, but loses much valuable information.

However, evidence for effects of historic preservation on gentrifying neighbourhoods is mixed. Using bivariate, multivariate and Poisson Count regression models with extent of historic designation in a census tract as dependent variable, Coulson and Leichenko (2003) find historically designated neighbourhoods in Fort Worth, Texas, have not demonstrated significant change in demographic composition, while such areas fare worse on neighbourhood indicators than areas without historic designations.

2.4. Assessing Impact of Built Heritage on Property Value

Historic preservation contribute to rising property values as part of gentrifying pressures for several reasons. Heritage conservation could be embedded within broader neighbourhood rejuvenation programmes (Kong and Yeoh, 1994) boasting attractive amenities such as plazas and mixed-use developments enhancing the area’s perceived desirability (Tan and Ti, 2020). Secondly, rising values may stem from perceived prestige tied to ownership of a ‘rare’ commodity and implicit guarantee a neighbourhood will retain its ‘authenticity’ and aesthetic appearance into the future (Rypkema, 2008). Third, consumption and cultural preferences of the affluent middle-class for supposed ‘authentic’ and aestheticized experiences of urban heritage (Mathews and Picton, 2014) encourage their flight into historic neighbourhoods with exorbitant residential property values wielded as symbolic expressions of high cultural and economic capital (Bourdieu, 1985).

Numerous studies affirm the positive relationship between built heritage designations with house price premiums. Focussing on inner cities in the US, Helms (2003) finds neighbourhoods with a concentration of gentrification and house restoration works tend to comprise low-density houses with historic and architectural merit, such as Brownstone houses in Brooklyn. Similarly, Lees (1994) affirms historic conservation is positively tied to housing investment in New York and London. In Shanghai, Arkaraprasertkul (2018) finds historic preservation of old lilong houses is mobilised by home owners turned rentiers to capitalise on higher rental values as a source of income.

2.4.1. Heritage Conservation in House Price Studies

According to Ley et al (2002), changes in population composition are reflected through pricing patterns within local housing markets, rendering hedonic pricing studies the dominant approach in existing literature to estimate price effects of historic preservation on residential properties. However, while many authors have studied separately the impact of built heritage conservation on house prices or on demographic change, prevailing research design in existing studies usually falls short of examining impacts of historic preservation on housing markets from the lens of gentrification.

Nonetheless, various authors employ OLS regression methods to study determinants or explanatory variables of change in housing prices over time, the latter taken as indication of gentrification. For example, Ley (1986) attempts to explain gentrification in inner cities by exploring changes in housing market and amenity value arising from heritage preservation. Ley et al's (2002) multivariate analysis of changes in dwelling values at census tract level for each metropolitan area in Toronto and Vancouver, Canada, further finds property market hot spots are concentrated in the city centre and in older districts. Similarly, Thomas (2018) regresses change in house prices in Chicago against change in neighbourhood amenities between 2000 and 2010.

However, these studies face two main limitations. First, despite attempting to isolate the impact of gentrification on house prices, they have not all considered specific effects of heritage conservation. Moreover, an Ordinary Least Squares (OLS) specification assumes independence of observations (Anselin and Bera, 1998), thus neglecting spatial autocorrelation, which house prices notoriously exhibit, where sale price of a property is affected by that of neighbouring properties (Franco and Macdonald, 2018).

It is therefore crucial to examine other studies employing a range of spatial hedonic regressions to examine impacts of built heritage conservation on sale prices of residential properties, even if not explicitly situated in gentrified neighbourhoods. Using a hedonic pricing model controlling for fixed-effects on a 5-year dataset of housing, Moro et al (2013) estimate as distance of a property to a built heritage site increases by 100m, sale price increases between 0.4-0.7% in Greater Dublin, Ireland. However, they find this effect varies depending on the type of heritage site – While historic buildings and memorials confer positive externalities on surrounding residential properties, others such as archaeological sites constitute a negative amenity. Lazrak et al (2014) alternatively employs a spatial lag, error and Durbin models to study effect of designation on listed properties themselves in Zaanstad, Netherlands, simultaneously finding houses sold within a conservation area benefit from a premium of 26.4 %. Franco and Macdonald (2018) estimate in Lisbon, Portugal, conservation areas yield 4.1% premiums with spill-over benefits at 3.3% using a hedonic spatial error model with Mixed Geographically Weighted Regression to control for spatial non-stationarity. However, although authors generally concur historic preservation positively impacts property values, Sharpe (2006) disputes that historic designation has conferred premiums on surrounding properties in St.John's, Newfoundland.

A particularly novel and notable study attempting to explore built heritage value from residential property prices in Singapore is Tan and Ti's (2020) recent work. Using a modified repeat sales approach comparing resale values of residential units within a single housing block, they examine varying effects of built heritage on private property prices over a different distance buffers. They report, properties located in zones within 800m to 1.6km from a conserved site experience strongest price premiums over more distant zones. Tan and Ti (2000) acknowledge potential gentrification pressures engendered through URA's gazetting of conservation sites, albeit not the study's focus, but urge future work to illuminate such neighbourhood-level social and demographic changes.

Despite abundance of house price studies situated in Singapore considering the economic value of various amenities, built heritage has scarcely emerged as a topic of study. Nonetheless, it remains crucial to examine the former's insight into other house price determinants in Singapore, and avoid potentially exaggerating impact of heritage designation on housing values. A summary of other explanatory variables potentially influencing house prices, adapted from Lehner (2011), is presented in Table 2 (Fan et al, 2006; Mo, 2014).

Table 2. *Summary of variables used in hedonic house price studies on Singapore*

House Price Determinants	**Variables Represented**	**Authors**
Structural Variables	• Floor Area • Age • Floor level • Main Upgrading Program	Lehner (2011), Sue and Wong (2010), Nam and Lee (2019), Mo (2014)
Public transport	• Distance to nearest bus stop • Distance to nearest MRT station	Lehner (2011), van Eggermond et al (2011)
Private transport	• Distance to nearest car park	Lehner (2011)
Shopping	• Distance to nearest shopping mall	Lehner (2011), Addae-Dapah and Lan (2010)
Daily supply	• Distance to nearest supermarket • Distance to nearest hawker centre	Lehner (2011)

Work places	• Distance to central business district	Lehner (2011), van Eggermond et al (2011)
Education	• Distance to nearest primary school • Distance to nearest top primary school	Lehner (2011)
Leisure	• Distance to nearest park	Belcher and Chisholm (2018)

2.5. Existing Gaps in Literature

Overall, although there are presently studies attempting to assess the economic value of built heritage by examining residential property markets, literature remains largely dominated by work on effects of historic designations on neighbourhood-level changes and house prices in isolation, without attempts to integrate all three elements. Indeed, this appears to posit an ‘impossible trinity’, as Steif (2004:116) argues, amidst limited empirical data for neighbourhood-level housing markets, it has increased difficulties in modelling neighbourhood change occurring in tandem with micro-level housing markets, with most quantitative housing market research has elided changes in composition of residents themselves.

This paper similarly considers it deeply important to examine other accompanying neighbourhood changes pertaining to demographic profile of residents. However, within Singapore as study area, despite qualitative approaches to identify manifestations and effects of gentrification, there is discernible lack of quantitative studies to support such claims, exacerbated by sparse systematic attempts to trace spatial and temporal patterns of neighbourhood gentrification that contextualise gentrification processes to Singapore. Simultaneously, poor levels of academic insight into price effects of built heritage on house premiums in Singapore continues to obscure economic value of built heritage in gentrified neighbourhoods, despite vast potential for using housing market transaction data to explore this, blunting the edge of gentrification literature to aid more robust policy-making.

Responding to Tan and Ti (2020), this paper seeks to bridge these gaps by mapping the gentrification landscape over space and time in an East Asian city like Singapore, and uncovering statistical relationships between housing premiums in gentrified areas and conserved heritage sites.

3. Data and Methodology

3.1. Data Sources and Pre-Processing

All data, code and outputs used are accessible via an online repository. Data was obtained from data.gov.sg, Department of Statistics and OneMap Singapore, Singapore's lead portals for distributing open and publicly-available data.

3.1.1. Department of Statistics Census Data and General Household Survey

Census datasets published by Singapore's Department of Statistics are aggregated at planning area level, Singapore's main administrative zone. A range of themes covering characteristics of resident populations, households and working persons (Fig.1) for years 2000, 2010 and 2015 were obtained.

***Figure 1**. Map of Singapore's 55 planning areas*

However, several problems were encountered during data collection. First, data provided for planning areas is inconsistent between 2000 and 2010 Census of Population and mid-decade 2015 General Household Survey (2015). While

Singapore’s land area is subdivided into 55 planning areas to facilitate development planning, figures for some variables for particular planning areas were excluded from 2015 GHS. Section 3.2 details how this is addressed.

Some planning areas such as Punggol, an area of reclaimed land, only emerged after 2010, which if included, creates inconsistencies in subsequent cluster analysis undertaken. Other areas to which this similarly applies are Changi, Singapore River, Mandai, and are removed prior to analysis. Other planning areas such as Central Catchment Reserve, uninhabited and inappropriate for analysis, were excluded. A total of 32 planning areas are retained for analysis.

3.1.2. Resale Flat Transactions and OneMap Location Data

Resale flat transactions at individual property-level released by the Housing Development Board (HDB) only from 2014 to 2016 were obtained. This is due to computational constraints of the software employed, and policy changes within Singapore’s property market exacted by HDB prior to 2014. As part of cooling measures, new resale procedures were implemented, suggesting property price trends prior to could have been artificially inflated. The analysis controls for this by restricting transactions to those falling within this time period. Based on quarterly HDB Resale Price Index, resale flat prices from 2014 onwards display relative stability, minimising outliers potentially biasing results. Resale transactions released by HDB cover only public flats and not private properties, which are beyond the paper’s scope.

Variables in the dataset prior to pre-processing are shown below.

Table 3. *Original resale flats transaction dataset*

Variable	**Type**
Month	Datetime YYYY-MM
Town	Character
Flat Type	Character
Block	Numeric

Street Name	Character
Storey Range	Character
Floor Area Square Metres	Numeric
Remaining Lease	Numeric
Resale Price	Numeric

Despite considerable information on structural properties, the dataset contains only block number and street name of public flats. These addresses were geocoded for their coordinates through querying the API service from One Map Singapore, an authoritative and highly comprehensive mapping tool developed by Singapore Land Authority. As it also lacks information on locational and neighbourhood-level attributes of flats, e.g. proximity to amenities such as heritage goods, locations (centroids) of gazetted conservations areas were obtained from URA (Fig.2).

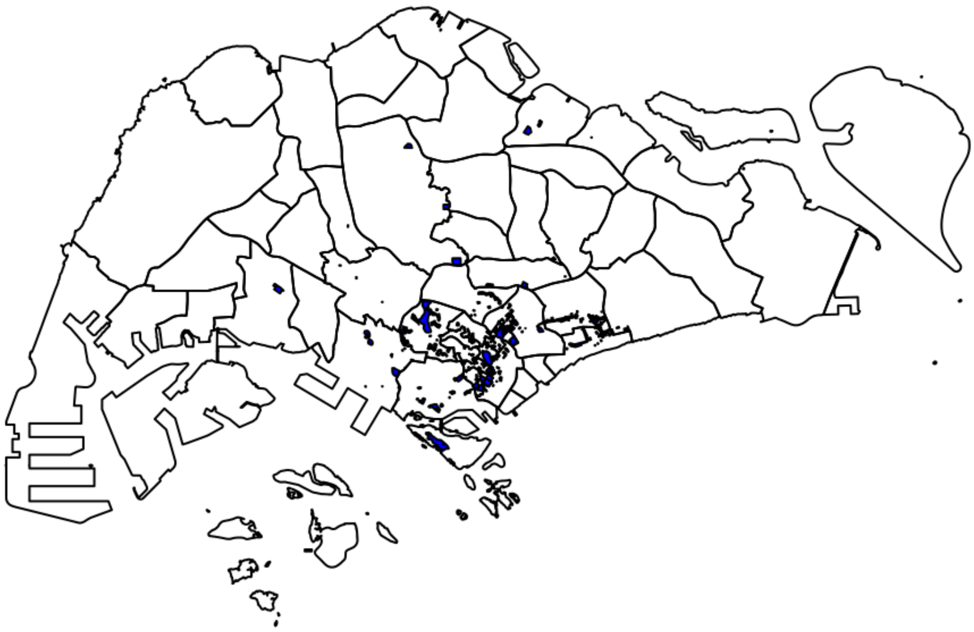


Figure 2. *Map showing location of Singapore's conservation areas*

Locational information on other amenities were retrieved from One Map Singapore:

- MRT Stations
- Bus Stops
- Shopping Malls

- Hawker Centres
- HDB Carparks
- Supermarkets
- Parks and Green Spaces

Information on prestigious primary schools was compiled based on primary schools which have received awards from the Ministry of Education, and likewise queried using One Map API service.

3.2. Illustration of Workflow and Methods

Fig.3 illustrates the integration of various methods, including clustering algorithms and building of regression models, into various stages of the workflow. All data pre-processing and cleaning was executed using Python, with subsequent analysis performed in R.

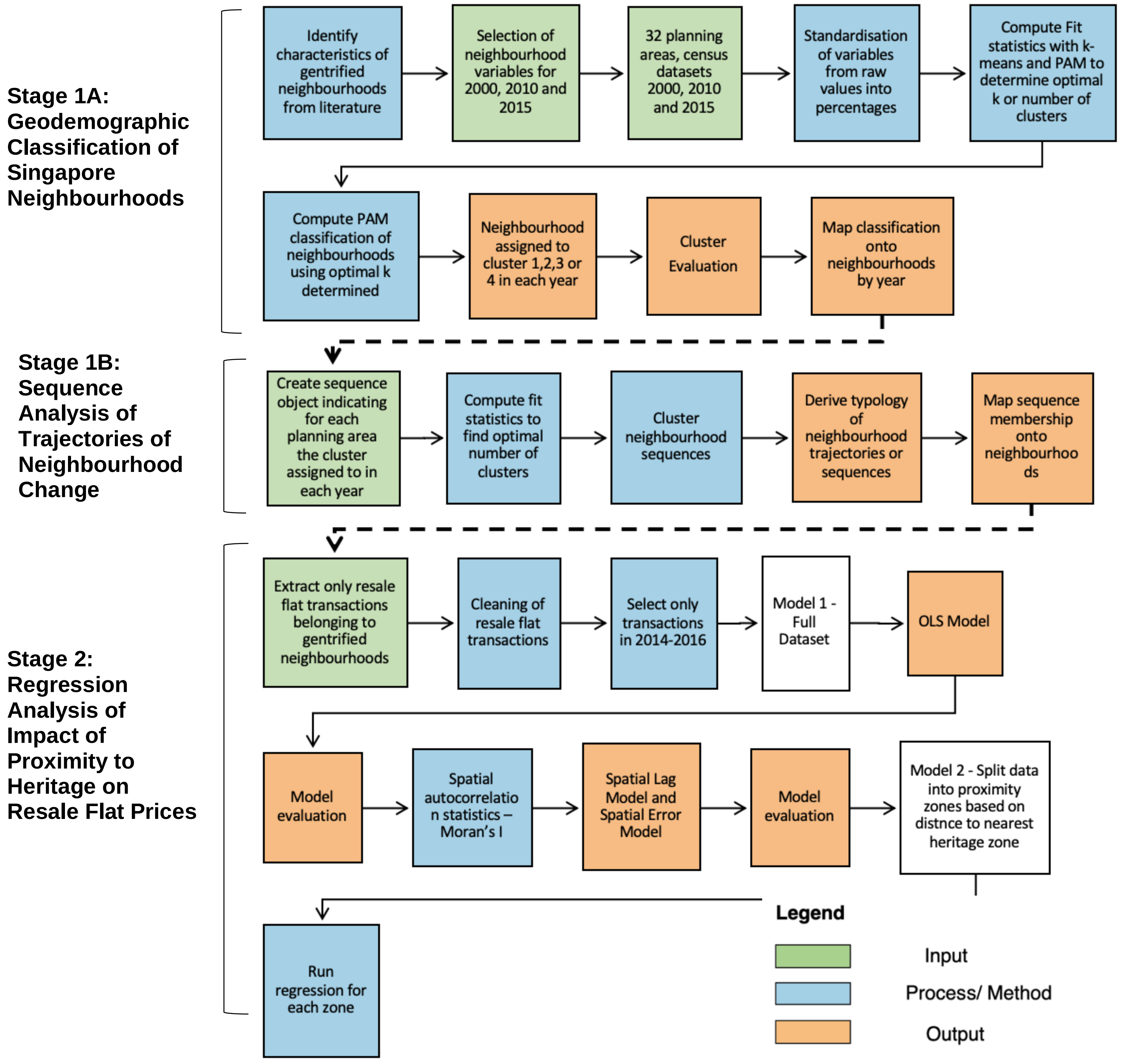


***Figure 3**. Overview of methodological process*

3.3. Stage 1A: Geodemographic Classification of Singapore's Neighbourhoods Using PAM Clustering

Following Delmelle (2016) and Ling and Delmelle (2016), a geodemographic classification of neighbourhoods from 2000 to 2015 into discrete, mutually-exclusive classes was produced to identify 'gentrified' or 'gentrifying' areas based on a selection of socio-economic, demographic and dwelling variables. Geodemographics, according to Rothman (1989:1), is “the classification of small areas according to their inhabitants" for predominantly commercial and policy purposes such as consumer or neighbourhood targeting. It is rooted in the underlying principle that inhabitants residing within the same neighbourhood or locality exhibit similar socio-economic and lifestyle attributes (Debenham et al, 2003), such that class, or social stratification, becomes spatialised (Parker et al, 2007), thus making it particularly relevant to the question of the geography of gentrification in Singapore (Smith and Butler, 2007).

In contrast to well-established systems of classification already present in the UK, such as Experian’s Mosaic and ACORN, such an undertaking is relatively novel in Singapore. Thus, despite technical criticisms surrounding this method (Debenham et al, 2003), in particular the Modifiable Areal Unit Problem (MAUP) where different aggregation of spatial units produces highly variable results (Openshaw, 1983), the method remains highly appropriate as much of these concerns are directed towards highly-granular geodemographic systems projecting wider neighbourhood characteristics from individual-level consumer data (Harris, 1998). Nonetheless, it is acknowledged the geodemographic classification produced here would be more comprehensive and informative if clustering was performed on subzone division areas rather than planning areas. However, this is constrained by unavailability of census data at a finer spatial resolution.

The workflow adopted is inspired by Ling and Delmelle (2016), who apply the K-Means clustering algorithm, to classify neighbourhoods based on selected variables in each time period. Such data should be rescaled for comparability across different dimensions, normally distributed and not highly correlated (Kaufman and Rousseuw, 2009). This involved conversion of raw values into percentages to account for differing sizes of planning areas, facilitating comparability across different neighbourhoods, negating need for rescaling data as percentages are bounded between 0 and 100. Variables selected were guided by prior studies, and modified based on literature on characteristics of ‘gentrifiers’ in Singapore’s context.

Inconsistency and discrepancies in census data collection between 2010 and 2015, required aggregation of income categories beyond S$8,000 provided in 2015 to match categories from previous years, although this potentially obscures further variation and interesting patterns. Additionally, despite interest in median resale flat values, these could not be used as input variables due to unavailability for year 2000, with missing data for some planning areas in other years. Moreover, median resale values are reported quarterly and disaggregated by flat type, with missing values for some flat types, such that difficulty in standardising values across all planning areas meant they had to be abandoned. Finally, although 2015 GHS curiously excluded information for some planning areas, removing these neighbourhoods from analysis would result in much loss of valuable information. Thus, their cluster assignments in 2015 were extrapolated from 2010.

In total, 32 neighbourhoods and 35 input variables for 2000, 2010 and 2015 were entered into the clustering process (Table 4).

Table 4. *35 input variables for cluster analysis of Singapore's planning areas*

Variable	**Composition**
Age Group (Years)	
% 0-19	Aggregated from categories age 0-4, 5-9, 10-14, 15-19
% 20-49	Aggregated from categories age 20-24,25-29,30-34,35-39,40-44,45-49
% 50-64	
% 64 % Over	
Monthly Gross Household Income from Work	
% Below S$1000	
% S$1,000 - $1,999	
% S$2,000 - $2,999	
% S$3,000 - $3,999	
% S$4,000 - $4,999	
% S$5,000 - $5,999	
% S$6,000 - $6,999	

% S$7,000 - $7,999 % S$8,000 & Over	Aggregated from categories of income brackets (intervals of S$999) from $8,000 to $20,000 & Over for Year 2015
Education Level / Highest Qualification Attained % Other Professional Qualification and Diploma % University Degree	
Ethnic Composition % Chinese % Malay % Indian % Eurasian and Others	
Occupation % Legislators, Senior Managers, Officials % Professionals	
Dwelling Type % HDB 1 to 3 Room % HDB 4, 5 Room & Executive % Condominiums % Landed Dwellings	
Household Structure % No Family Nucleus % Single Family Nucleus	
Household Size % 1 Person % 2 Person	

Contrary to Ling and Delmelle (2016), however, Partitioning Around Medoids (PAM) clustering algorithm, recommended by Brunsdon et al (2016), was deployed instead of K-Means. PAM is similar to K-Means in partitioning a dataset into k groups or clusters, but offers more robustness due to reduced sensitivity to noise and outliers (Kaufman and Rousseeuw, 1990). In PAM, cluster medoids – representative data points within a cluster – where average dissimilarity between it and all other cluster members are minimised, are used to compute clusters instead of an artificially-constructed mean value (cluster centroid) in K-Means (Kaufman and Rousseeuw, 1990).

Yet, similar to K-Means, it requires user specification of number of clusters to be generated. Optimal k was determined using elbow plots using various fit statistics to compute PAM algorithm with different k values. Within-clusters sum of squares indicates compactness of clustering, so minimising it minimises variation within clusters (Kassambara, 2017). Lebart et al's (2000) D-index, measures clustering gain from intra-cluster inertia, i.e. similarity of data within a cluster, by calculating distances between representative centroids and other data points. Optimal k is shown by significant knee in first differences of clustering gain or peak in second differences of clustering gain against number of clusters (Charrad et al, 2014: 14). Across the plots, optimal k appeared to be 4. Post-diagnostic visual inspection of clusters and silhouette scores were calculated for every classification.

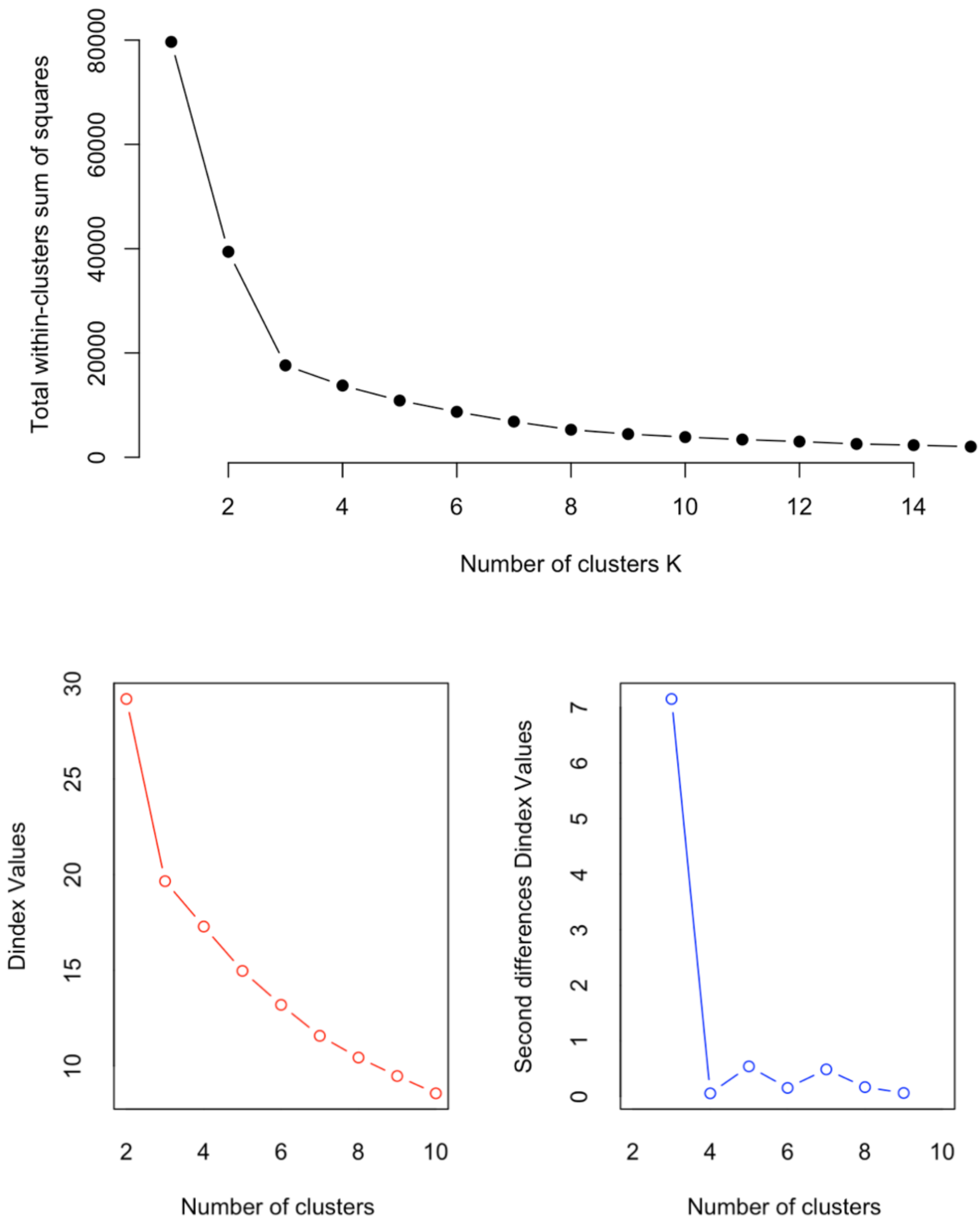


Figure 4. *Elbow plots with different fit statistics*

3.4. Stage 1B: Mining Neighbourhood Trajectories with Sequence Analysis

Patias et al (2019) suggest, geodemographic classifications are ultimately based on comparing patterns at discrete time stops, instead of exploring sequential patterns of events over time. Thus, pairing the former with analysis of sequences of ‘states’, originally developed for analysing DNA sequences and measuring their similarities (Sanger and Nicklen, 1977), can further illuminate diversity of representative neighbourhood transitions as achieved by Delmelle (2016).

The workflow presented is adapted from Patias’ (2019) reproducible online notebook using sequence analysis to explore trajectories of long-term youth unemployment in Europe. Using TraMineR in R, a sequence object was created based on cluster groups neighbourhoods were assigned to in each year. Using the simple Optimal Matching Algorithm, sequence dissimilarity is measured by calculating ‘distances’ or substitution costs between each pair of sequences needed to transform one sequence into another (Abbott and Tsay, 2000), deriving a dissimilarity matrix in Fig.5, showing probability of transitioning from Cluster 1 to 4 is slightly lower than probability of transitioning from Cluster 1 to 3.

	1->	2->	3->	4->
1->	0.000000	1.744444	1.826389	1.819444
2->	1.744444	0.000000	0.962500	1.725000
3->	1.826389	0.962500	0.000000	1.500000
4->	1.819444	1.725000	1.500000	0.000000

Figure 5. *Pair-wise sequence dissimilarity computed for sequence object*

Subsequently, PAM clustering is again applied to these sequences, with optimal k determined using earlier explained methods (Patias, 2019). Visualisation of sequence plots and maps of sequence trajectories enables identification of Singaporean neighbourhoods demonstrating pathways of ‘upgrading’ representative of gentrification.

3.5. Stage 2: Exploring the Price Effect of Built Heritage on Resale Values Using Regression Models

A total of 7,508 resale flat transactions are analysed, after filtering the dataset to those neighbourhoods identified as gentrified according to the neighbourhood specified in the ‘Town’ variable (Table 3). Isolation of these neighbourhoods is based on the expectation that price effects of conserved heritage on property values here are most pronounced. As explained, resale transactions are restricted to those within 2014-2016 only, due to mammoth size of original dataset and policy changes in the resale market. Moreover, active gazetting of heritage sites prior to this period minimises potential for spuriously attributing price effects to other neighbourhood developments.

3.5.1. Hedonic Pricing Models

This paper adopts a hedonic pricing regression model, a well-established regression technique presuming residential units comprise a ‘bundle’ of attributes with varying utilities (Rosen, 1974; Freeman, 1979), namely different structural, environmental and neighbourhood characteristics. Although without directly observable market values, each have an implicit market price influencing the price consumers are willing to pay for a particular property (Chin and Foong, 2006). In conventional practice, parameters of a hedonic price model are calibrated with an Ordinary Least Squares estimator (Malpezzi, 2002), assuming independence and absence of spatial dependence among observations with identical distribution (Cao et al, 2018). It takes the form specified below, with Y_i as the dependent variable (resale price), βi represent regression coefficients, with X_i as explanatory characteristics such as housing structural attributes, location and environmental characteristics, and ε representing the error term (Lehner et al, 2011).

$$Y_i = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \varepsilon_i, \varepsilon_i \sim \text{iid}N\left(0,\ \sigma^2\right) \quad (1)$$

3.5.2. Accounting for Spatial Autocorrelation in Hedonic Pricing Models

However, Dubin (1998) highlights, house prices usually exhibit positive spatial autocorrelation, where geographically proximate or nearby houses tend to exhibit similar values. OLS specifications of hedonic pricing models neglect accounting for spatial dependence and autocorrelation of residuals arising from geographic datasets (Cao et al, 2018), potentially producing biased, coefficients (Anselin and Bera, 1998). To address this, two commonly-used methods deployed here are explained below.

3.5.2.1. Spatial Lag Model

Spatial lag models (SLM) include a spatial lag term to correct for spatial dependence presumed to be inherent in the response variable itself (Anselin, 2001), where house price at one location is affected by the price of a neighbouring house.

$$Y = \alpha + \rho WY + \beta X + \varepsilon, \varepsilon \sim \text{iidN}\left(0, \sigma^2 I\right) \quad (2)$$

The specification above eliminates interference arising from spatial autocorrelation by introducing a spatially-lagged dependent variable ρWY, with Rho as the spatial autocorrelation coefficient, W as the spatial weights matrix relating the sale price of a flat to sale prices of other flats within the specified neighbourhood of each flat (Wang and Ready, 2005). Whether or not the Rho variable equals 0 determines if spatial autocorrelation exists in the SLM (Wang et al, 2019).

3.5.2.2. Spatial Error Model

According to Wang and Ready (2005:7), while SLM presumes a flat’s own price directly influences sale prices of neighbouring houses, spatial error models (SEM) suggest location factors influencing a flat’s selling price also influence the selling price of neighbouring houses. Thus, SEMs posit spatial dependence enters the error term through either through exclusion of omitted variables or measurement error in location variables (King, 1987; Anselin and Rey, 1991; Wang and Ready, 2005), correcting this by adding a spatial autoregressive error term where spatial autoregressive coefficient λ is multiplied by a spatial weights matrix W.

$$Y = \alpha + \beta X + \varepsilon, \text{ with } \varepsilon = \lambda W \varepsilon + \xi, \ \xi \sim iidN\left(0, \sigma^2\right) \quad (3)$$

λ is a measure of spatial autocorrelation in neighbouring residuals (Ward and Gledisch, 2008).

3.5.3. Data Pre-processing and Workflow

As the original transactions dataset offers sparse information on locational and environmental attributes of flats, feature engineering was carried out to create variables denoting distance between a flat to various amenities potentially influencing resale prices. This involved a nearest neighbour search of the nearest site to each resale flat and computation of Euclidean distance (in metres) between these two points, with a Python script adapted from Tenkanen and Heikinheimo (2019), for points of interest listed below:

- Conserved Heritage Sites
- MRT Stations
- Bus Stops
- Shopping Malls
- Hawker Centres
- HDB Carparks
- Supermarkets
- Parks and Green Spaces

Final variables used in the regressions are summarised in Table 5.

Table 5. *Input variables for hedonic regression models*

Variable	**Unit of Measurement**
HDB Resale Price (Dependent Variable)	Singapore dollars

Remaining Lease	Years
Year	Month and Year of Transaction
Floor Area	Square Metres
Flat Model (*Dummies)* Adjoined Flat Apartment Improved Maisonette Model A Model A-Maisonette New Generation *(reference)* Premium Apartment Simplified Standard DBSS	
Flat Type (*Dummies)* 1 ROOM 2 ROOM 3 ROOM (Reference) 5 ROOM EXECUTIVE	
Town town_ANG MO KIO (*reference)* town_BUKIT MERAH town_BUKIT TIMAH town_CLEMENTI town_GEYLANG town_MARINE PARADE town_TOA PAYOH	
Floor Level / Storey	
Distance to nearest conservation site *(key independent variable)*	Metres

Distance to the CBD	Kilometres
Distance to nearest MRT station	Metres
Distance to nearest bus stop	Metres
Distance to nearest shopping mall	Metres
Distance to the nearest prestigious primary school	Metres
Distance to nearest hawker centre	Metres
Distance to nearest supermarket	Metres
Distance to nearest carpark	Metres
Distance to nearest carpark	Metres
Zone indicating distance buffer a flat location falls into *(Dummies)* 0-400m 400-800m 800-1200m 1200-1600m 1600-2000m Over 2000m	

To normalise distribution of dependent variable (Fig.6) and improve model interpretability, log transformation of resale price was carried out, with no further transformations of independent variables deemed necessary (Fig.7).

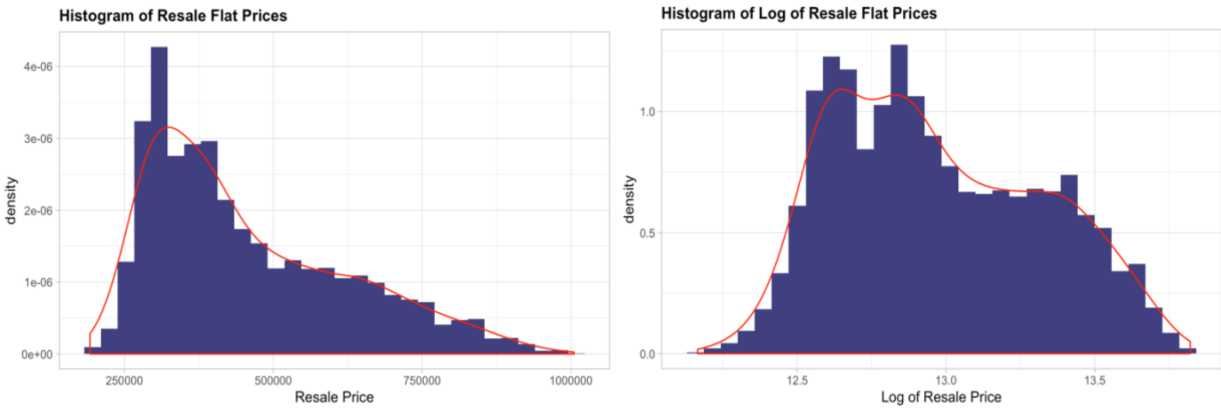


Figure 6. *Distribution of dependent variable before-after log transformation*

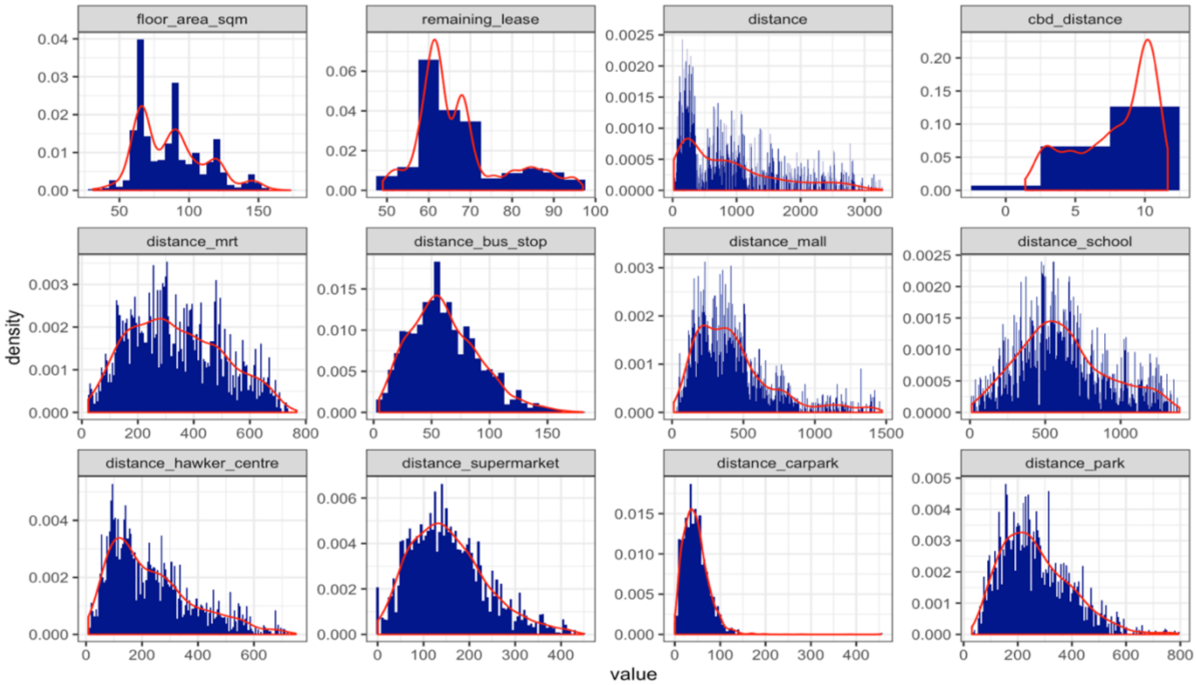


Figure 7. Distribution of continuous independent variables

Multicollinearity between variables were checked using Pearson and Variance Inflation Factor. While no severe multicollinearity was detected with Pearson's correlation coefficient, extremely high VIF values exceeded 10 for these variables: 'floor_area_sqm', 'cbd_distance' and 'flat_type_EXECUTIVE', which were removed from subsequent models.

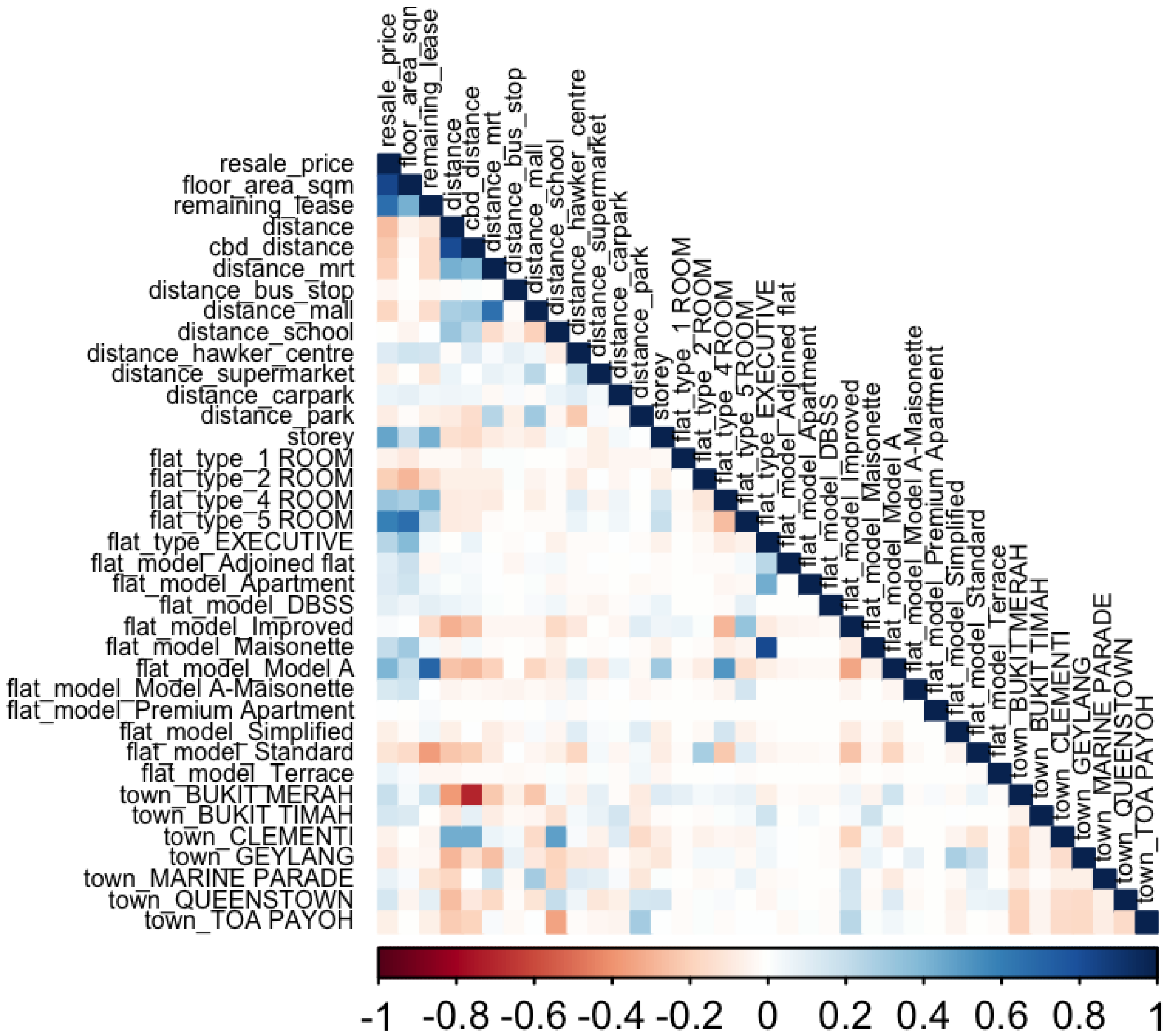


Figure 8. *Correlation matrix of regression input variables*

Two different model specifications exploring different dimensions of price effects of built heritage were constructed. Model 1 exploits the full dataset to explore the overall income yield of built heritage from house prices in gentrified neighbourhoods. However, to explore differential impacts of conserved heritage on resale prices at different distance buffers, i.e. distance decay effect of proximity to built heritage on resale prices, Model 2 splits the dataset into zones based on their proximity. Drawing on Tan and Ti's (2020) approach, input data for Model 2 is derived from splitting the full transactions dataset into different zonal groups. 5 zones were created – Zone 1 (0-400m), Zone 2 (400-800m), Zone 3 (800-1200m), Zone 4 (1200-1600m), Zone 5 (1600-2000m) – with regressions run separately for each zone group and results compared. In both specifications, each resale transaction is treated as a single temporal event.

Under the first specification, a baseline OLS log-linear regression model was created, using forward and backward stepwise selection to ensure the final model included only statistically significant variables. This stepwise selection was repeated for Model 2's regression models for each proximity zone. Residual spatial autocorrelation is checked for using the Moran's I test (Anselin, 1995), confirming appropriateness of implementing spatial lag and error models using the *spatialreg* package in R. However, one constraint encountered is existing packages are not equipped to handle spatial autocorrelation where a single location (e.g. HDB block) has multiple observations (different resale flats). Thus, a subset of data with only unique addresses or locations was used for computing spatial lag and error models, suggesting they should be cautiously compared to the baseline OLS model.

Following Lazrak et al (2013), a spatial weights matrix was computed using a distance measure which finds k nearest neighbours to each point, as resale transactions data consists of spatial points. Contiguity measures are usually applied when data consists of spatial polygons sharing borders, and inappropriate in this case (Getis and Aldstadt, 2004). Selection of optimal k was guided by autocorrelation plot showing when correlation between log of resale price of a flat and its neighbours decreases most dramatically (Fig.8).

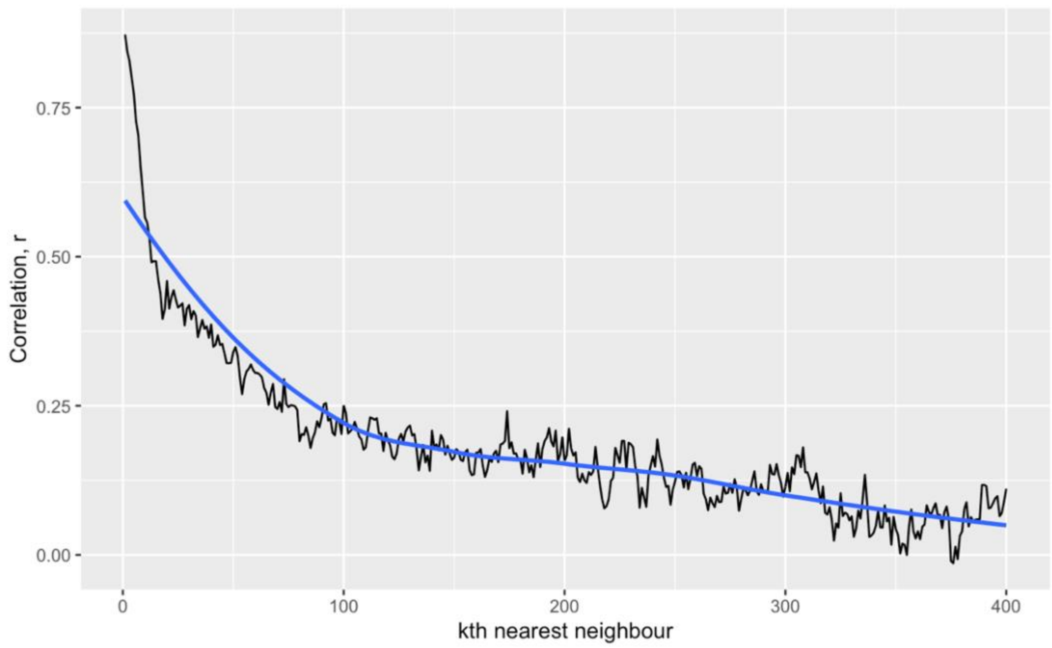


Figure 9. *Autocorrelation plot of nearest neighbours*

The level of similarity decreases drastically at the 100th nearest neighbour, leading to selection of k as 100 to compute the neighbours list, which is subsequently transformed into a spatial weights matrix for computing spatial residual autocorrelation in the OLS model, and in SEM and SLM models.

Robustness checks and evaluation of model fit were carried out for all models. To determine which alternative spatial regression model is most appropriate, the Lagrange-Multiplier Test was applied to distinguish between the spatial lag and error models. Anselin's (2005) recommended decision process for interpreting LM test statistics is summarised in Fig.9. Where both LM test statistics are insignificant, the OLS model is correct. If only one is significant, the model with a significant test statistic is selected. If both test statistics are significant, the Robust form of the statistics should be examined with similar principles applying. Should both Robust statistics be significant, the model with a higher test statistic or a higher order of magnitude of significance is selected (Anselin, 2005:199-200).

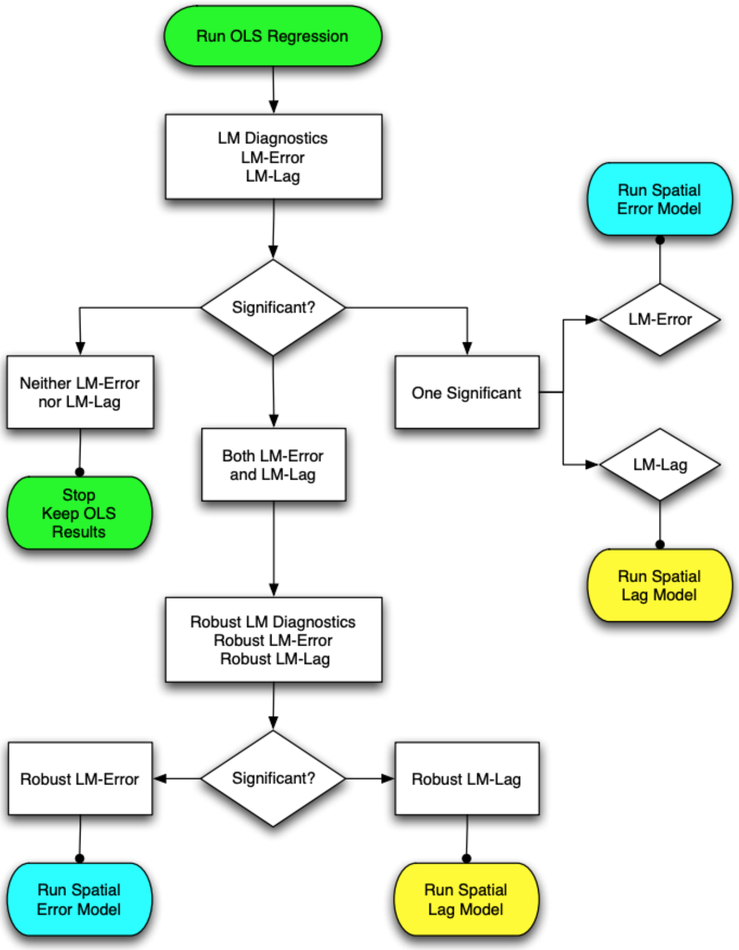


Figure 10. Decision process for determining spatial regression model (Anselin, 2005)

3.6. Ethical Reflection

The level of ethical risk in this investigation is considered minimal, as all data used is information published on Singapore's government-run open data portals easily accessible to any member of the public, and freely available in the public domain. Such information is made available to the public to make personal informed decisions of prospective property purchases, and for academic and commercial research. All records of sales transactions are anonymised and not tied to identifiable persons, with no concerns of accidental reveal of confidential or sensitive information. Low-level risks such as accidental or coincidental observation of known individuals is possible, but care has been taken not to disclose of such knowledge.

4. Analysis and Results

4.1. Spatial Patterns of Input Variables into Geodemographic Classification

Prior to examining the geodemographic classification, choropleth maps of Singapore's planning areas in 2000 and 2015 for key variables characteristic of gentrification are compared. The pattern consistently emerging is the dominance of centrally-located planning areas across income, educational qualification and occupational indicators (Fig. 10-12).

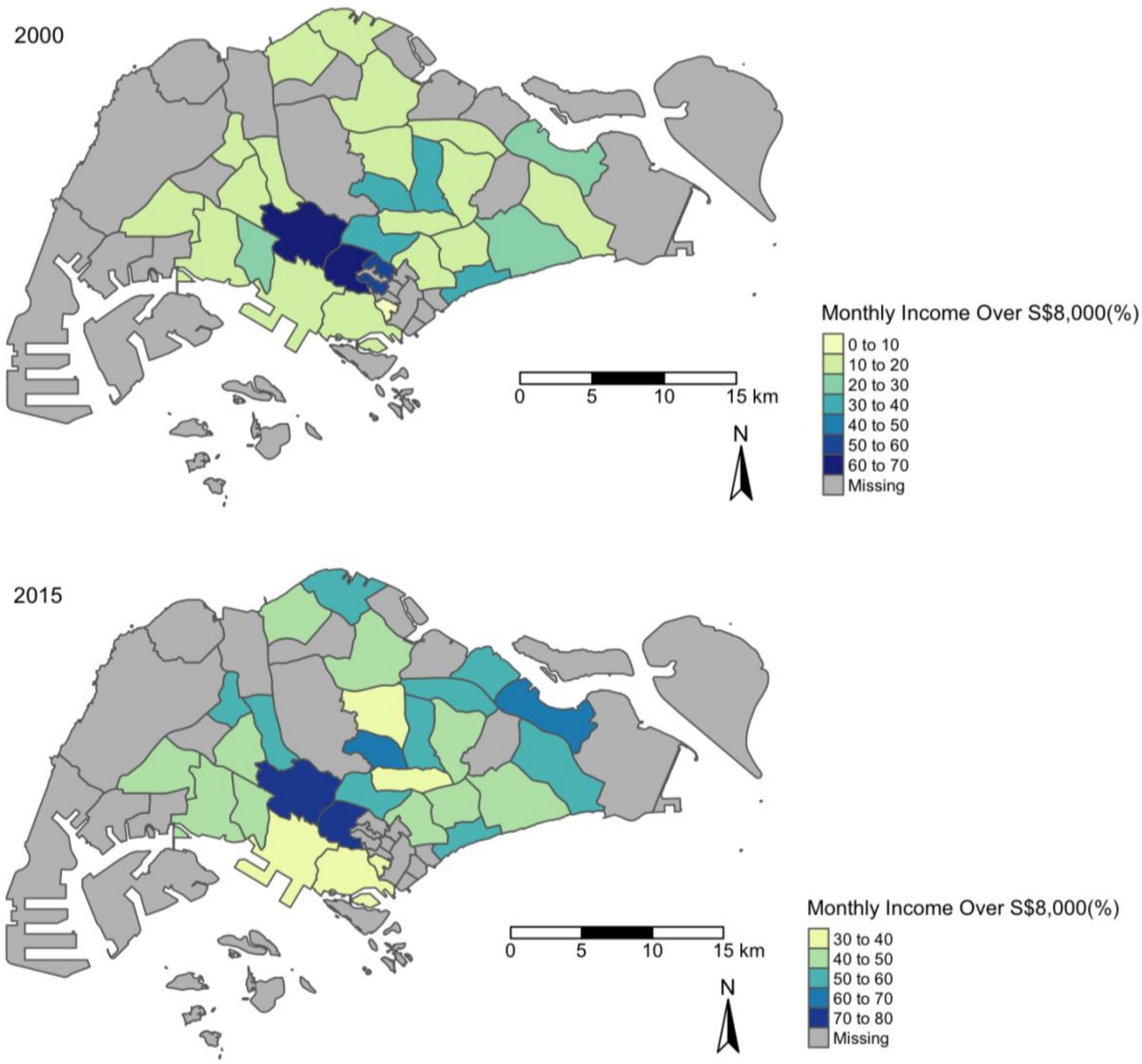


Figure 11. *Comparison of percentage of households with income over $8000 by planning area in 2000 and 2015*

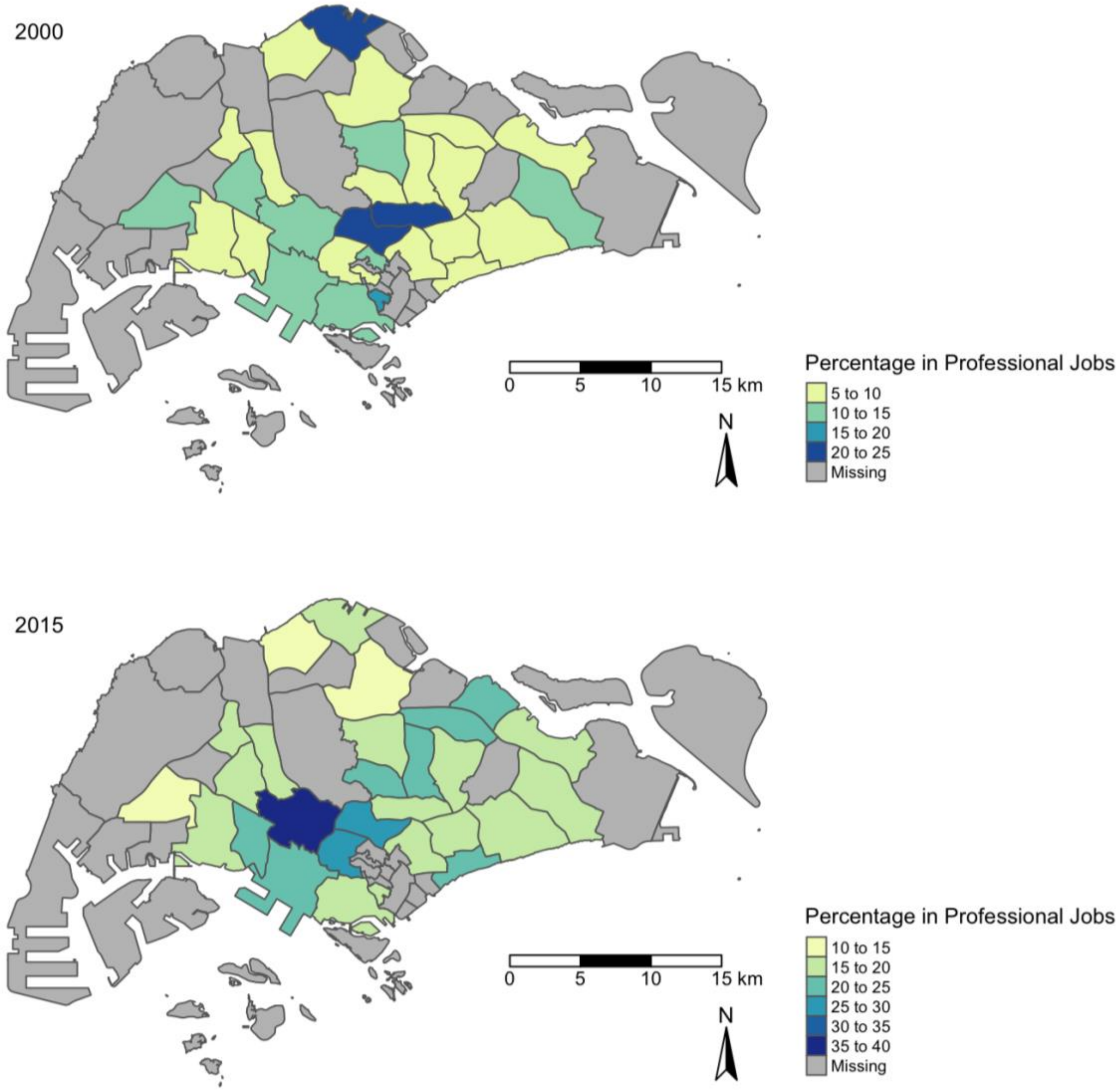


Figure 12. *Comparison of percentage of working persons in white-collar professions by planning area in 2000 and 2015*

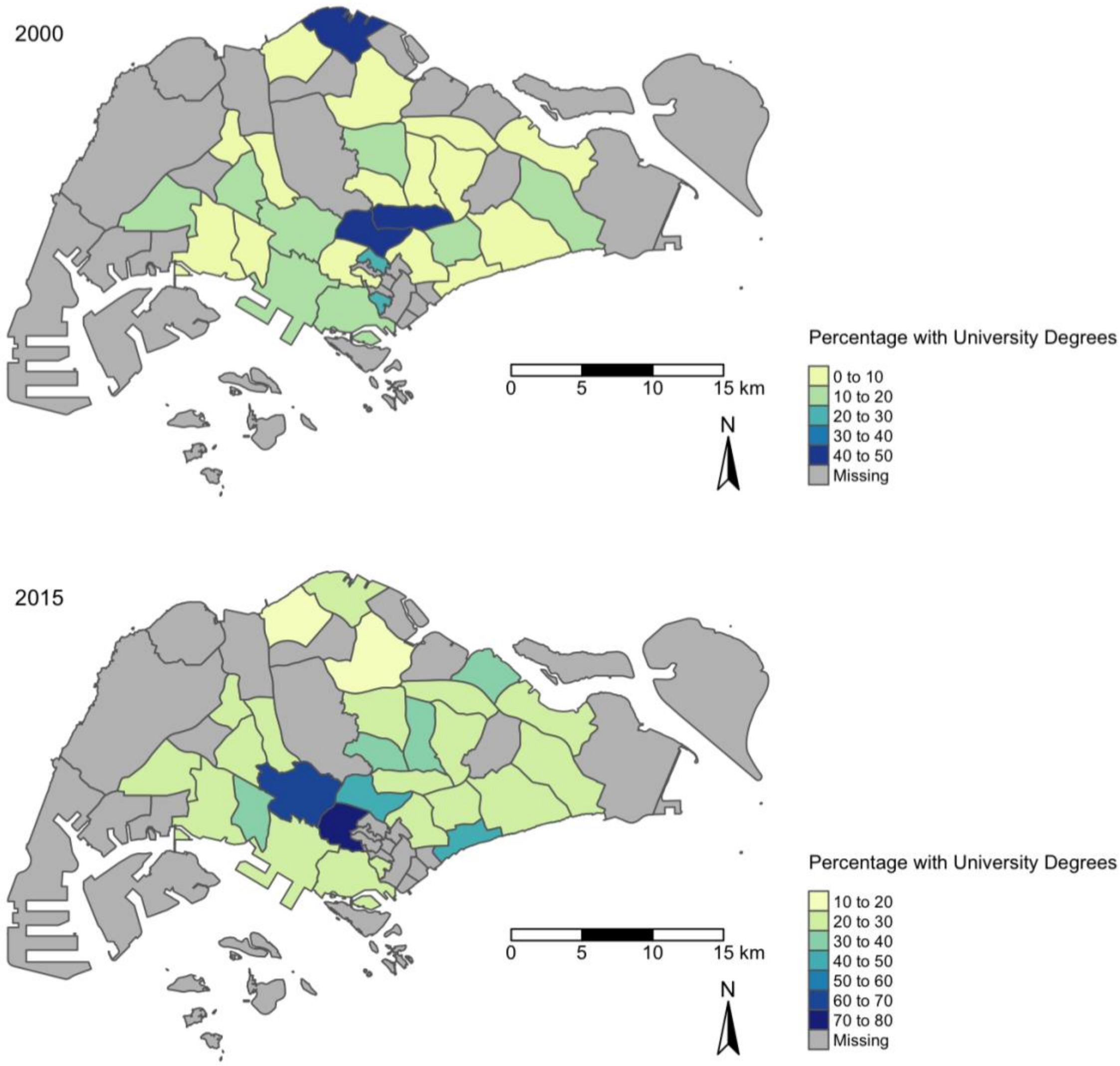


Figure 13. *Comparison of percentage of working persons with university degrees by planning area in 2000 and 2015*

However, planning areas showing consistently high values have shifted between 2000 and 2015, although there is a tendency for planning areas which are centrally situated to demonstrate higher proportions of potential gentrifiers. In contrast, peripheral planning areas consistently reflect low values in these characteristic indicators.

4.2. Assessing Clustering Tendency of Singapore's Neighbourhoods

Table 6. *Comparison of Hopkin's statistics for 2000-2015 census data*

Hopkin's Statistic	**2000**	0.8006704
	2010	0.7975138
	2015	0.6292078

The Hopkins statistics are fairly high and greater than the minimum threshold 0.5, giving confidence the census data is clusterable through all the periods examined, allowing rejection of the null hypothesis and conclusion the data has statistically significant clusters.

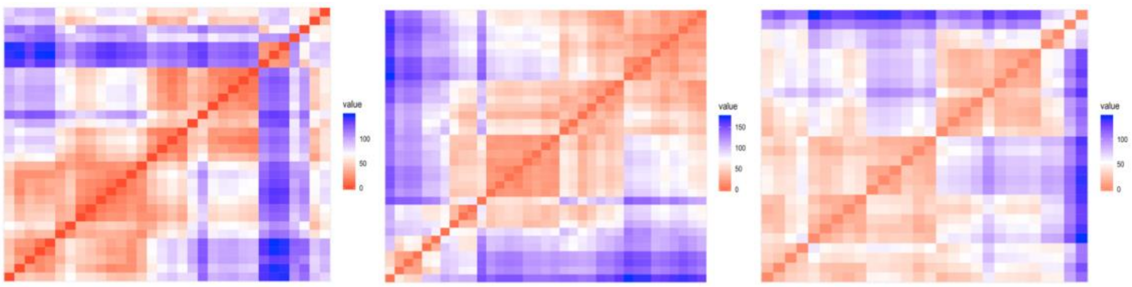


Figure 14. *Dissimilarity matrix for 2000, 2010 and 2015 census data*

Visualisation of the dissimilarity matrix, or distance matrix, of the input variables computes the distance between each pair of observations across all years. The plots reflect areas of high similarity in red (and hence, low dissimilarity) as well as areas of low similarity (i.e. high dissimilarity) in blue, providing preliminary indications of the presence of clusters in the data structure.

4.3. Geodemographic Classification of Neighbourhoods Between 2000 – 2015 with Partitioning Around Medoids (PAM)

Using PAM clustering, Singapore's neighbourhood typology derives four distinct neighbourhood classes, with the visualisation of clusters and their changing membership in 2000, 2010 and 2015 presented in Fig. 14, with these plots derived based on the two most important variable dimensions computed via Principal Component Analysis (PCA).

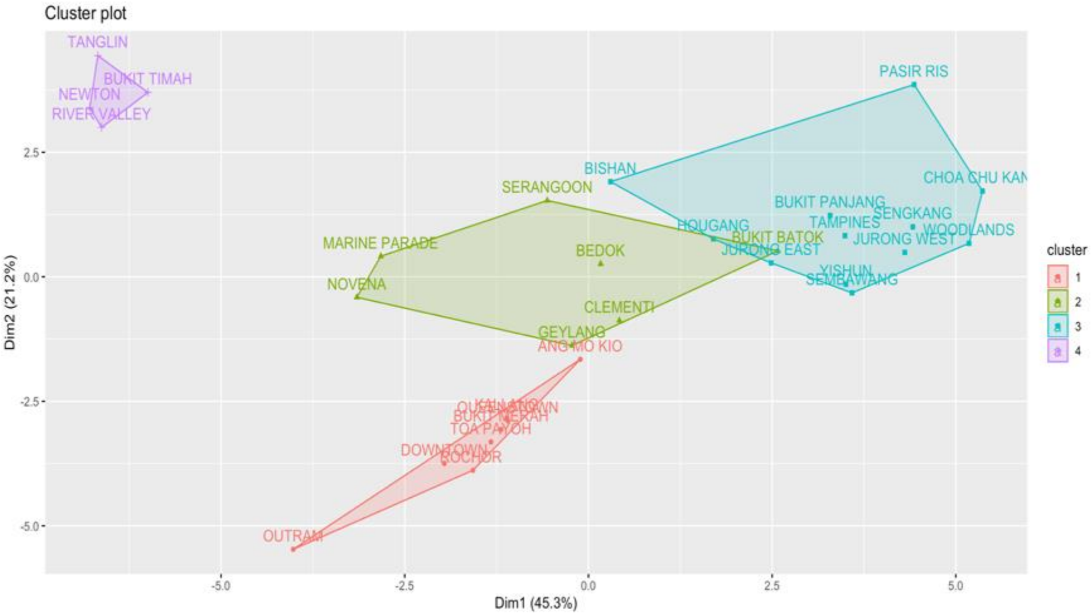


Figure 15. *Visual representation of cluster assignment of neighbourhoods in 2000*

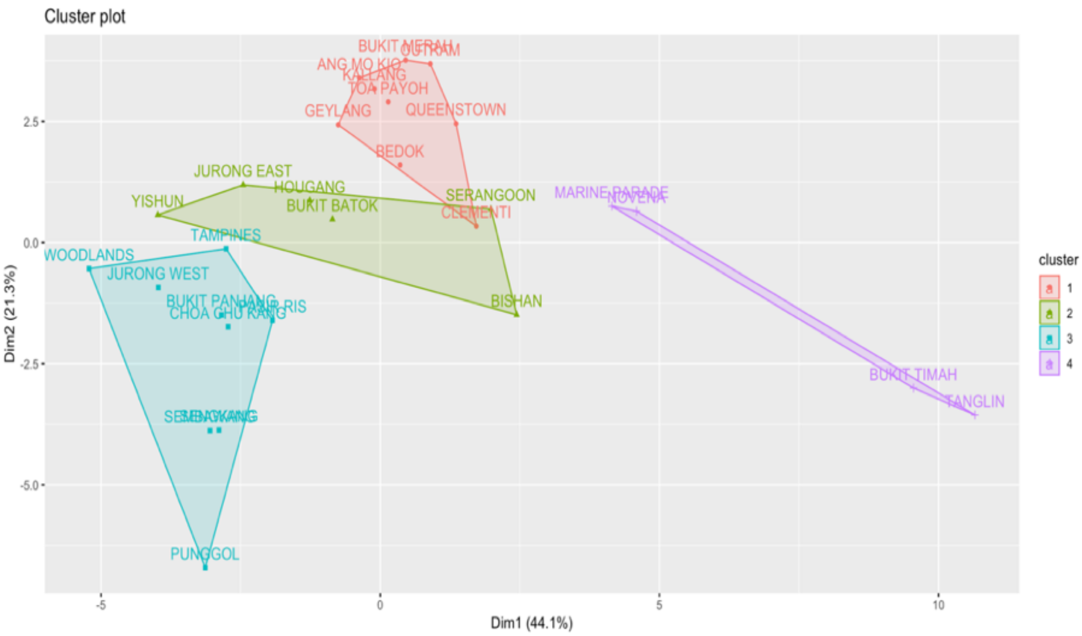


Figure 16. *Visual representation of cluster assignment of neighbourhoods in 2010*

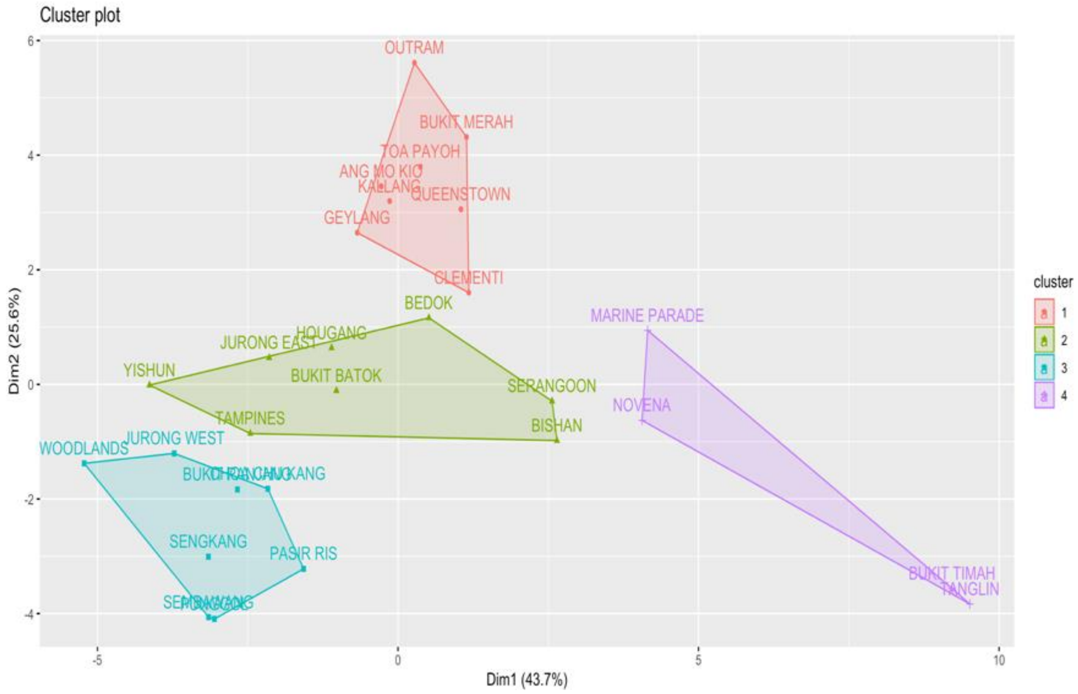


Figure 17. *Visual representation of cluster assignment of neighbourhoods in 2015*

Radar plots allow better insight into constituent characteristics and key differences across cluster, with their average values computed. Generally, Cluster 4 (Fig.21) represents neighbourhoods or planning areas which are most affluent, with consistently the largest percentage of households having a monthly income of $8000 and over exceeding 50%. On average, more than half of the neighbourhood population has a university degree. Similarly, Both Cluster 1 and 4 are most similar to having characteristics of gentrified neighbourhoods, with highest percentages of Eurasian and Chinese communities. Moreover, Cluster 4 consistently has largest percentages of condominiums and landed properties, consistently noted by Wong (2005) and Shin et al (2016) as characteristics of ‘new-build gentrification’ in East Asia, with a fairly young average population.

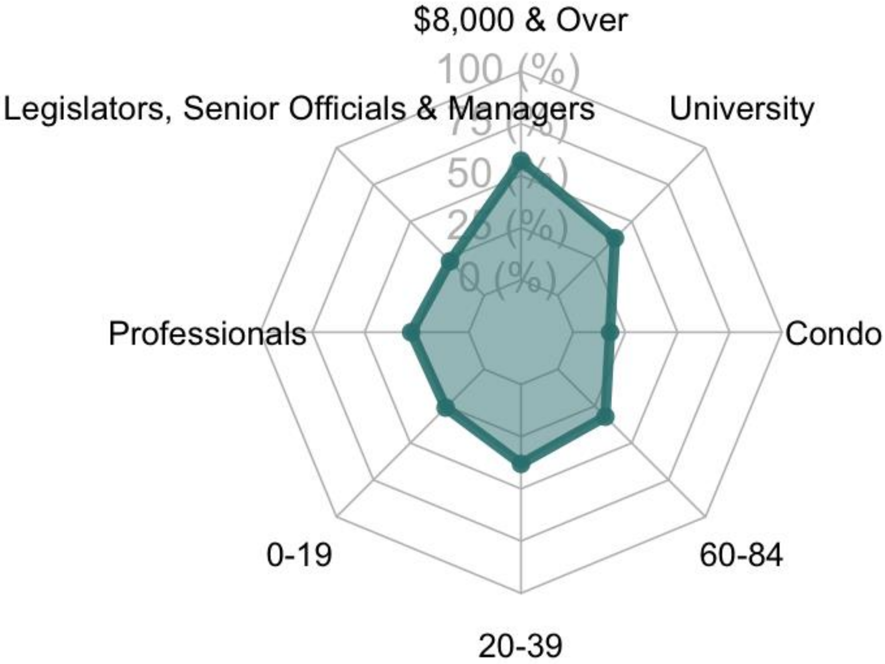


Figure 18. *Radar plot of cluster 1*

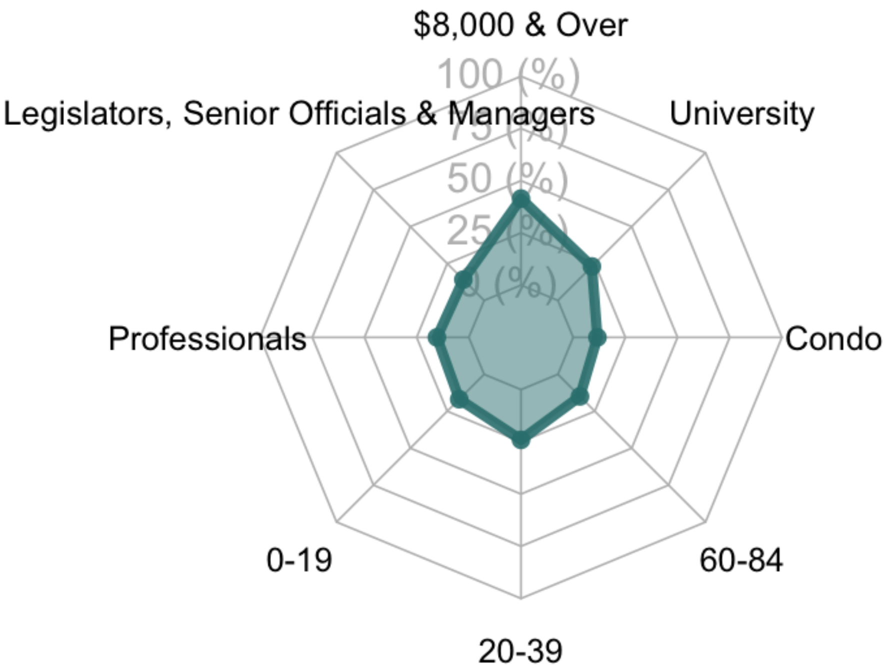


Figure 19. *Radar plot of cluster 2*

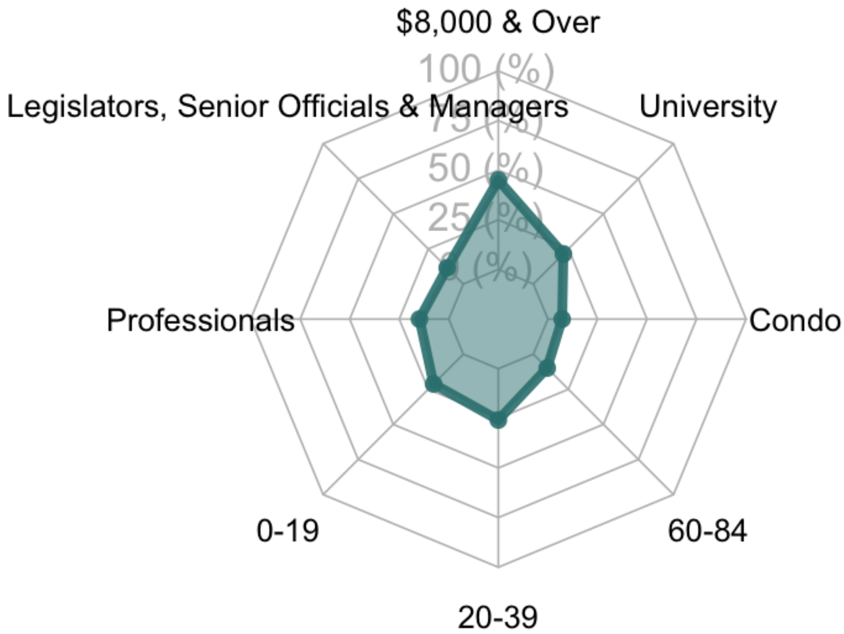


Figure 20. *Radar plot of cluster 3*

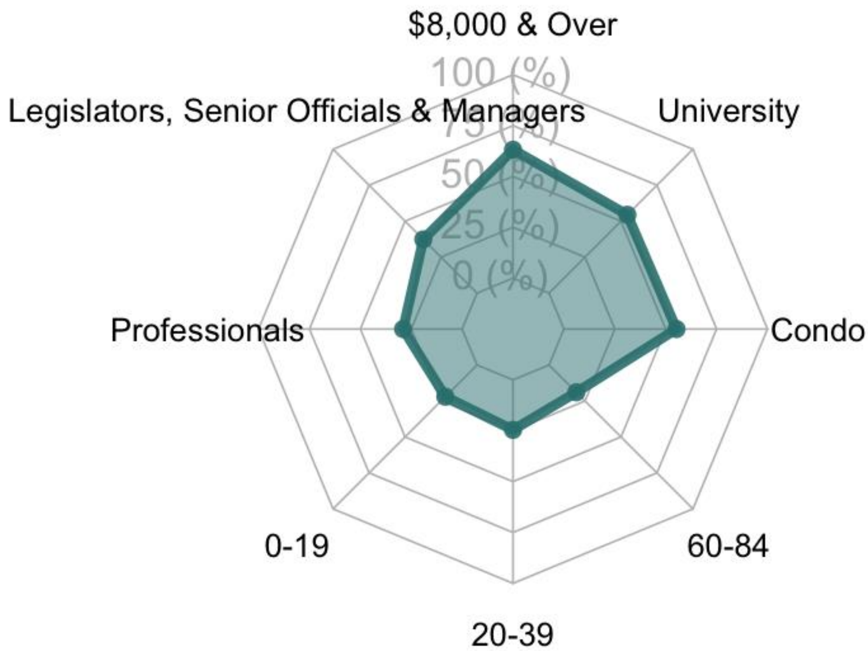


Figure 21. *Radar plot of cluster 4*

In contrast, Clusters 2 and 3 (Fig.19,20), despite exhibiting higher percentages of condominiums and landed properties than Cluster 1, perhaps due to larger sizes of planning areas, demonstrates lower percentages of those working white collar jobs such as professionals and managers, suggesting dominance of blue collar and manufacturing jobs. However, although Clusters 2 and 3 demonstrate relatively higher proportions of young people relative to the other clusters, this difference appears rather small. Notably, however, Cluster 1 and 4 simultaneously demonstrate larger proportions of elderly populations between 60-84 years in comparison to the latter two.

4.3.1. Spatial Patterning of Singapore's Neighbourhood Clusters

Several interesting patterns emerge from spatial analysis of Singapore' neighbourhood clusters. Firstly, ascent in cluster membership generally happens not to disparate neighbourhoods or those in isolation, but appears to affect adjacent neighbourhoods sharing a geographical boundary. This is consistent with Eckerd's (2011) observation that a strong predictor of gentrification is prior gentrification in a neighbourhood with which it shares a border (Guerrieri et al, 2013). From 2000 to 2010, several neighbourhoods including Novena, Geylang and Marine Parade, which lie next to each other, demonstrate upgrading from Cluster 2 to 1 or 4. Such upward neighbourhood transition is demonstrated strongly in planning areas closer to the downtown core, with Bukit Timah and Tanglin, both neighbourhoods richly endowed with heritage and cultural amenities, appearing to exert an outward 'gentrifying pull' on surrounding neighbourhoods (Fig.22-24).

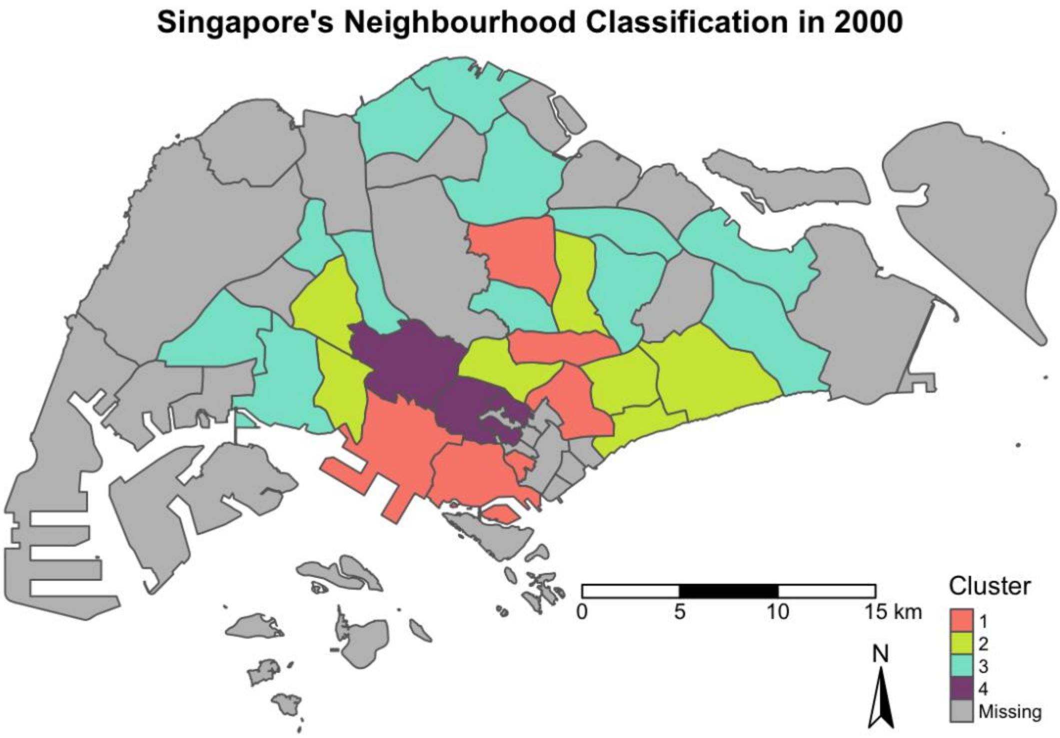


Figure 22. *Geodemographic classification of Singapore's neighbourhoods in 2000*

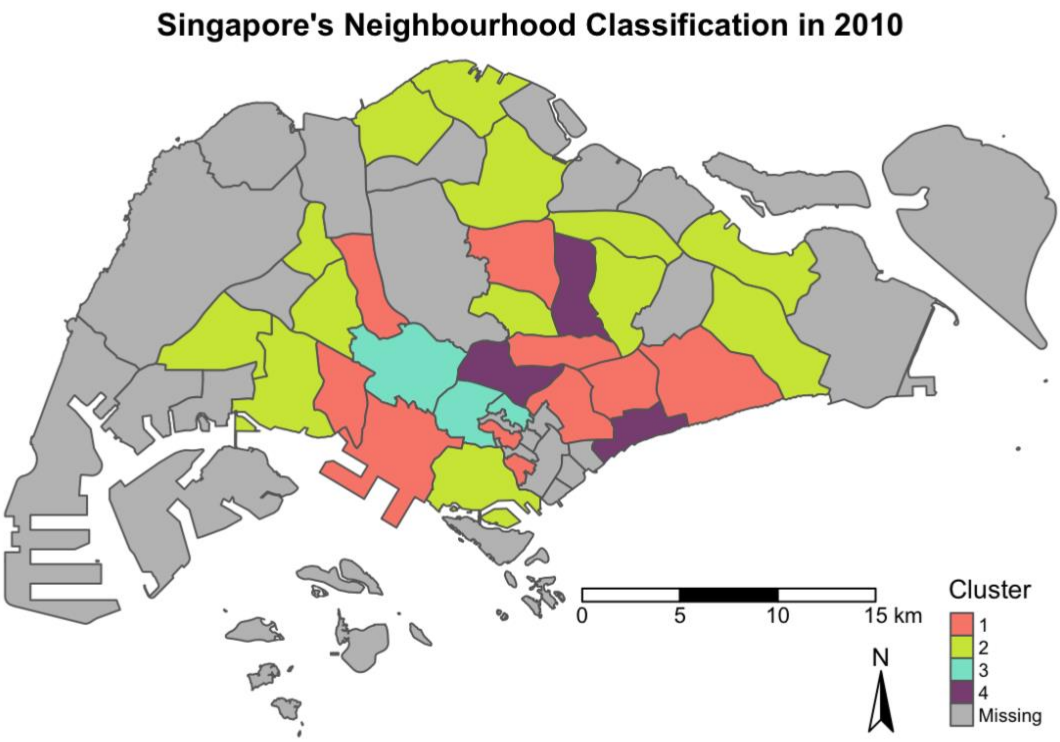


Figure 23. *Geodemographic classification of Singapore's neighbourhoods in 2010*

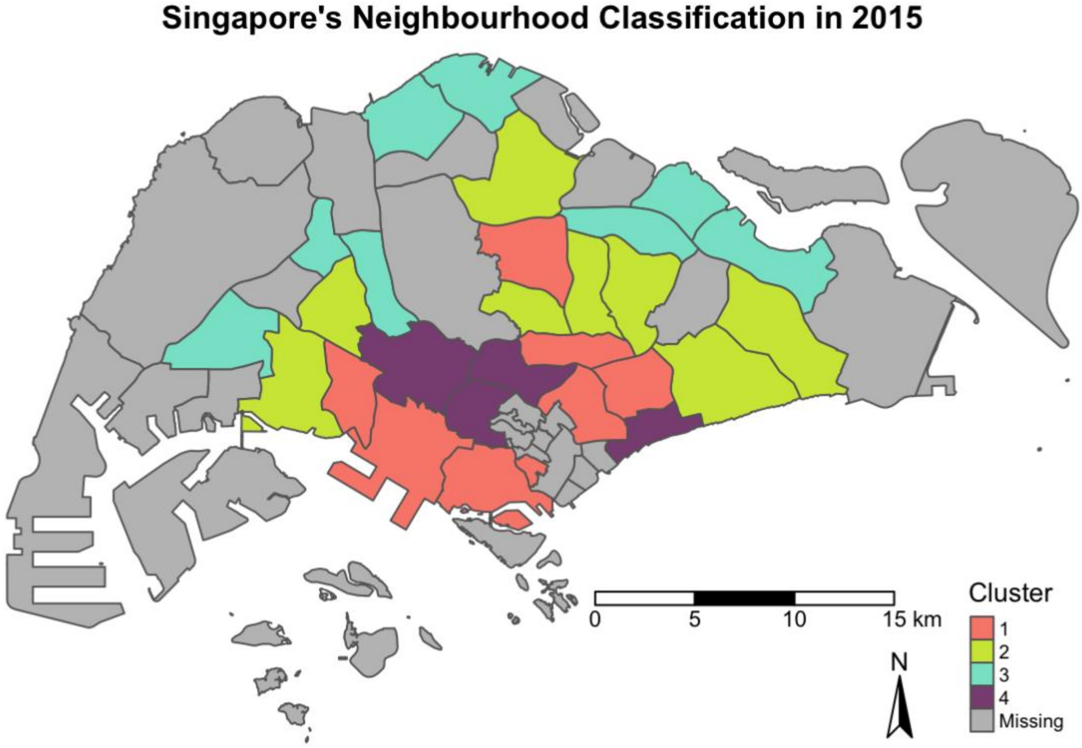


Figure 24. *Geodemographic classification of Singapore's neighbourhoods in 2015*

However, such neighbourhood transition has not been similarly observed in the suburban planning areas, which largely toggle between membership of Cluster 2 and 3, rather than exhibit clear patterns of neighbourhood ascent in socio-economic and demographic indicators. This constitutes prima facie evidence the distribution of neighbourhood classes may be influenced by existing distribution of heritage goods across Singapore's urban landscape. Spatial concentration of heritage goods in the city's central area may be creating 'pockets' of gentrified areas surrounding these amenities.

4.3.2. Clustering Validation

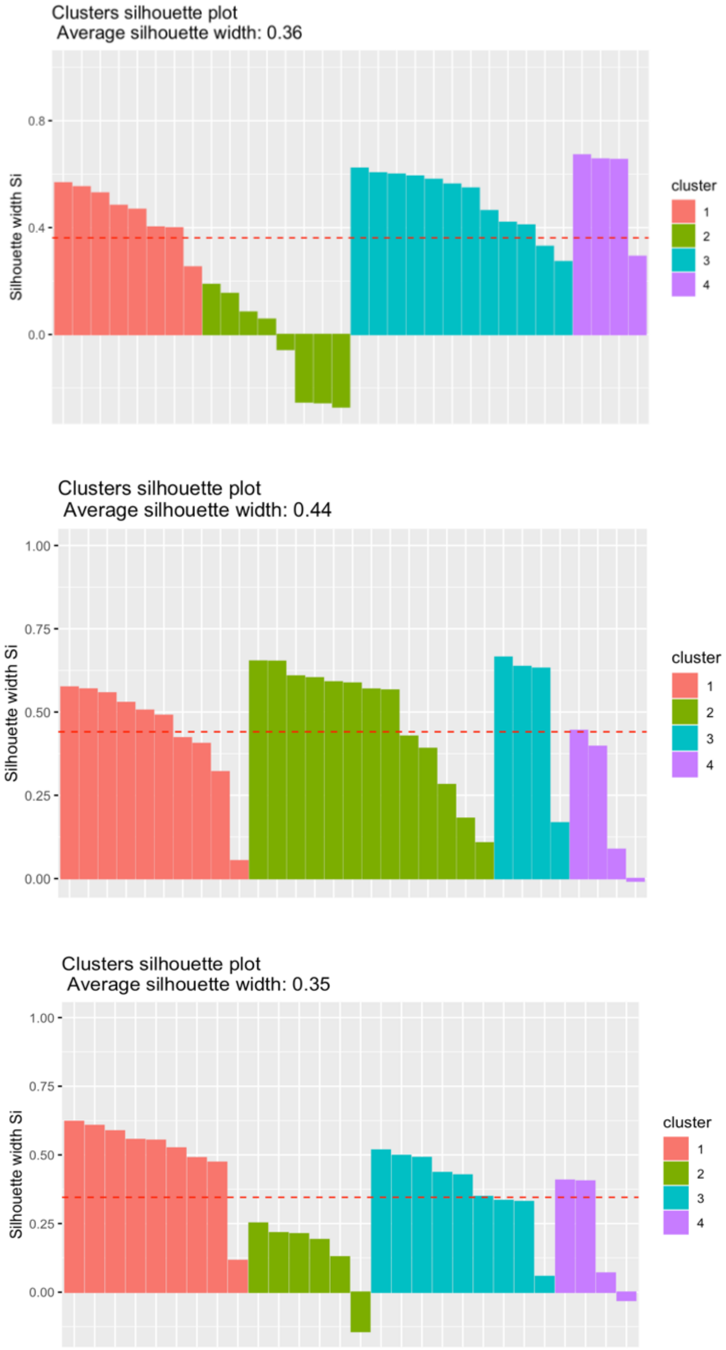


Figure 25. *Silhouette scores for geodemographic classification in 2000, 2010 and 2015*

Silhouette width is a measure of average distance between clusters (Rousseeuw, 1987). Average silhouette width of the clusters range from 0.35 to 0.44, indicating relatively good clustering quality achieved in the classifications. While there are some observations or neighbourhoods having negative silhouette score in 2000 and 2015, this does not necessarily cast doubt that k=4 is an optimal solution as moving objects to other clusters would decrease silhouette score of other clusters while violating rules of PAM clustering.

4.4. Discovering Singapore’s Neighbourhood Trajectories through Sequence Analysis

Fig.21 illustrates Singapore’s typology of neighbourhood change which consist of four representative trajectories emerging from the PAM clustering performed on neighbourhood sequences over 2000-2015. These sequences are:

(a) Sequence Cluster 1: Suburban to Highly Educated, White-Collar

Neighbourhoods within this group reflect a gradual transition from being grouped together with suburban neighbourhoods to those more closely mirroring gentrification patterns. These neighbourhoods constitute a ring around inner-most neighbourhoods of the city centre, the only exception being Ang Mo Kio which appears to be geographically isolated from other cluster members.

(b) Sequence Cluster 2: Stable Affluent

These neighbourhoods, although showing some potential for ascent into the gentrifying neighbourhood clusters, with some neighbourhoods demonstrating relative affluence and economic strength, ultimately show trajectories of stability between membership of Cluster 2 and 3, rather than experiencing upgrading. They comprise of neighbourhoods surrounding the first group, and are sandwiched between the third and first group.

(c) Sequence Cluster 3: Stable Suburban

These neighbourhoods, while highly similar in relative stability of socio-economic and demographic between 2000-2015 to the previous group, differ in their spatial location from the previous, and instead form an outer, peripheral ring around all other groups, and are located in the outermost fringes of Singapore.

(d) Sequence Cluster 4: Affluent to Elite

This group of consistently consistently-improving neighbourhoods on employment, income and educational indicators show relatively smooth, rapid transition into membership of Cluster 4, remaining in this cluster from 2010 to 2015, thus demonstrating 'gentrification' which disrupts conventional understandings of classical gentrification as transformation of working-class or areas of economic 'marginality' (Zukin, 1987). Rather, these neighbourhoods evolve from being merely affluent to exhibiting demographic changes reflective of gentrifiers, with increasing white-collar professionals and smaller household sizes and structure.

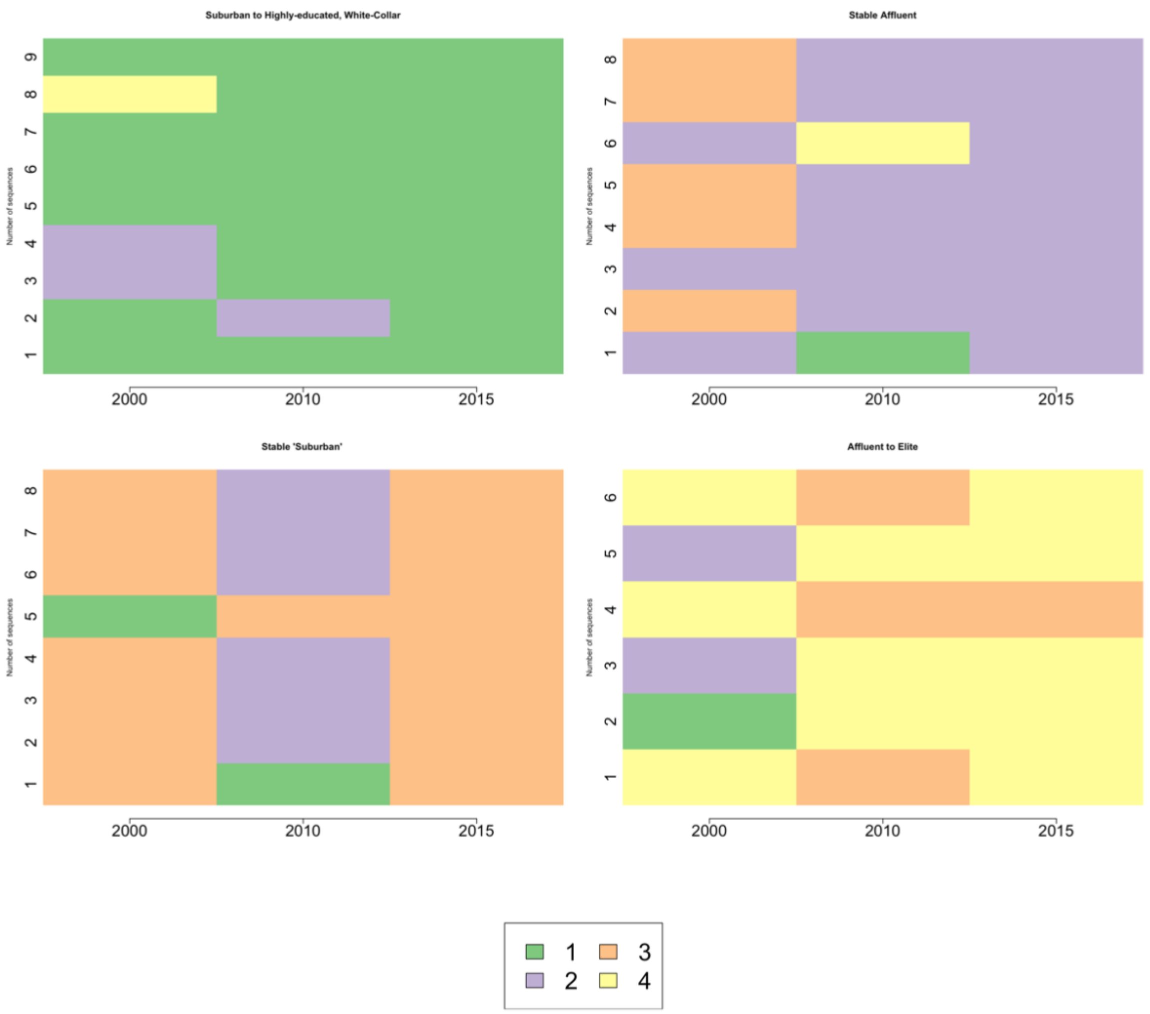


Figure 26. *Typology of neighbourhood change sequences in Singapore*

Overall, neighbourhoods belonging to the sequences 'Suburban to highly-educated white collar' and 'Affluent to elite' reflect clear patterns of neighbourhood upgrading overall, generally shifting from either Cluster 2 or 3 to Cluster 1 and 4. Mapping these sequences, neighbourhoods corresponding to these two sequences are concentrated around Singapore's central area, mirroring even the existing spatial distribution of conservation and heritage areas. These gentrifying neighbourhoods are identified as Ang Mo Kio, Clementi, Queenstown, Bukit Merah, Geylang, Kallang and Toa Payoh, as well as Bukit Timah, Tanglin, Novena, Marine Parade.

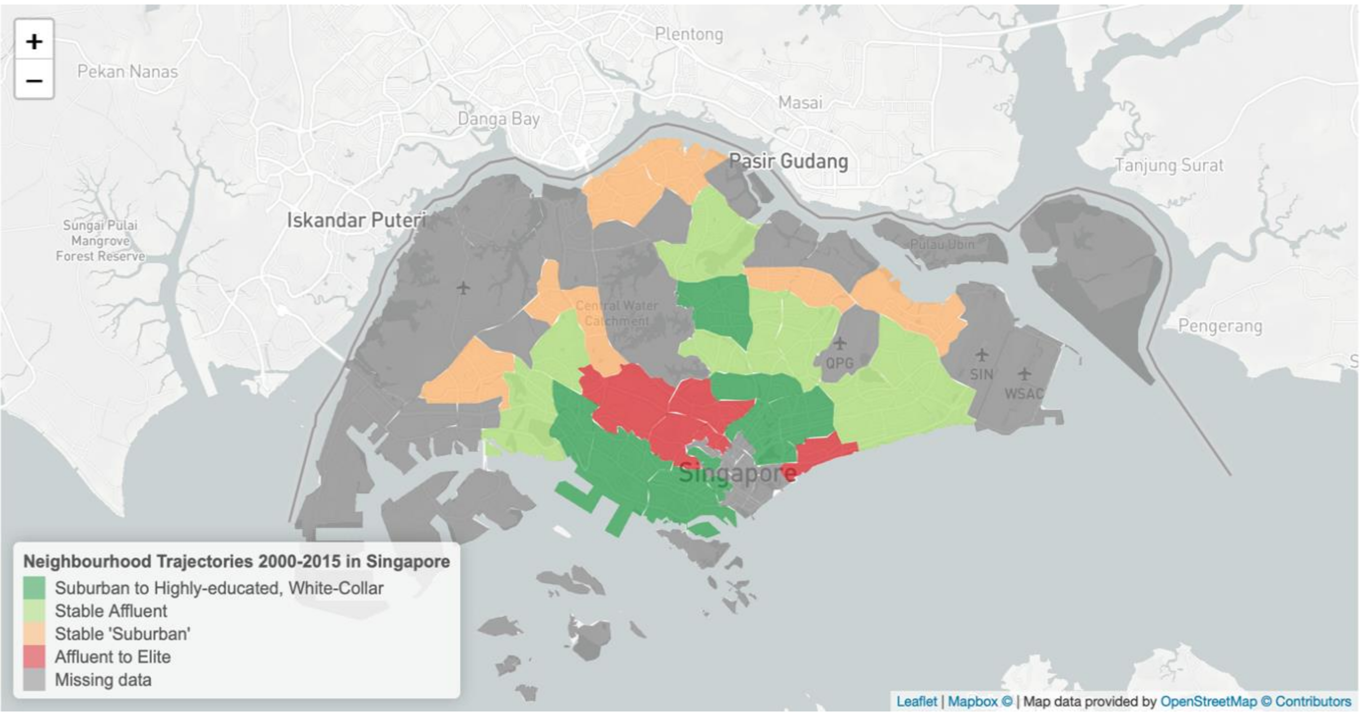


Figure 27. *Spatial locations of Singapore's neighbourhood trajectory sequences*

4.5. Estimating the Economic Value of Conserved Built Heritage from Resale Prices with OLS and Spatial Hedonic Pricing Regression

4.5.1. Resale Prices by Zone Groups

Using only data restricted to resold flats located in gentrified neighbourhoods corresponding to the sequence analysis and organising them according to their proximity to conserved heritage sites, preliminary examination of median resale values between different zone groups reveals substantial variation. Zone 1 (0-400m), comprising of flats closest to heritage sites, has highest median resale price, followed by Zones 2-5 in descending order. However, this effect seems to stagnate in Zone 3 (800-1200m) with median resale prices similar to Zone 2's.

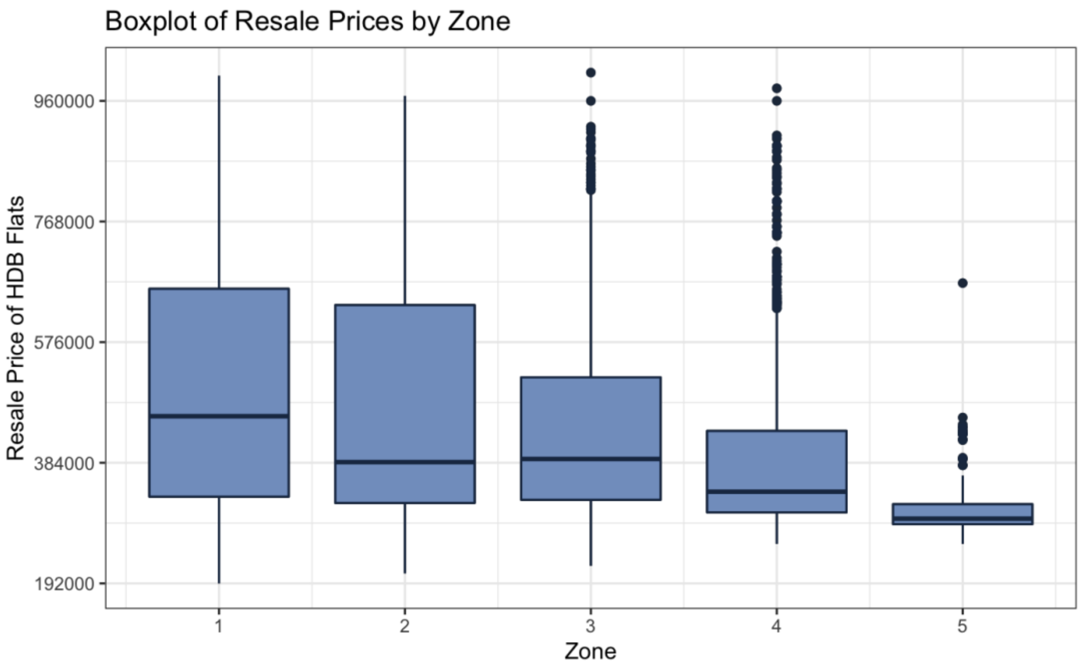


Figure 28. *Boxplot of resale flat prices by zone*

Contrary to expectations of a negative relationship between resale prices and distance to conservation areas, Zone 2 instead reflects a positive relationship. Nonetheless, this positive effect does not persist in subsequent regression models, suggesting inclusion of other explanatory variables of resale price mitigates such misleading observations.

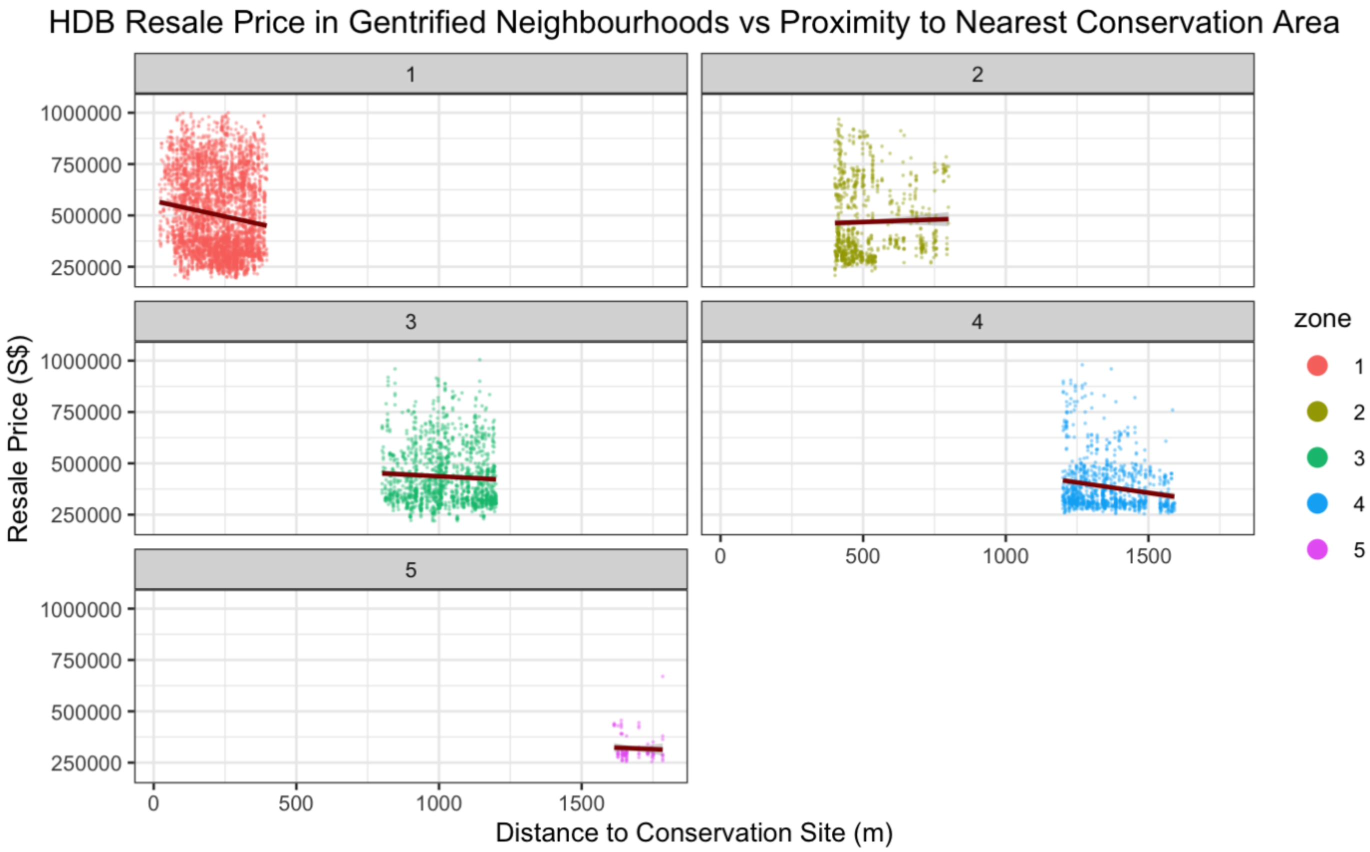


Figure 29. *Scatterplot of resale prices against distance to nearest conservation site by zone*

4.5.2. Model 1 – Price Effect of Conserved Heritage on Resale Flat Values

4.5.2.1. Comparison of OLS Baseline Model with Spatial Lag and Spatial Error Models

The results show proximity to built heritage gazetted for conservation is consistently statistically significant in influencing resale prices of public flats across OLS, SLM, SEM models. OLS Model 1 reflects, as distance to a heritage site increases by 1m, log of resale price of a public flat decreases by 0.0163%. The adjusted R-squared of the OLS model is also extremely impressive, suggesting the model explains 91.4% of variance in log of resale price, while statistically significant F-statistic indicates the model is good fit to the data. Nonetheless, the Moran's I test reveals some weak, positive residual spatial autocorrelation, computed based on correlation between the 100th nearest neighbours of a flat.

Table 7. *Moran's I test for residual spatial autocorrelation in OLS model*

Moran I Statistic	**p-value**
0.1401908	< 2.2e-16

Table 8. *Lagrange-Multiplier diagnostics for spatial dependence in SEM and SLM models*

	Test Statistic	Significance
LM Lag	248.03	< 2.2e-16
LM Error	1408.8	< 2.2e-16
Robust LM Lag	13.722	0.000212
Robust LM Error	1174.5	< 2.2e-16

However, based on Table 8, the spatial error model appears more appropriate relative to the spatial lag model, with the Robust LM-Error statistic being larger and having a smaller significance value than the Robust LM-Lag statistic, suggesting SEM estimates are more robust. Comparing estimates from SEM and SLM, parameter estimates for distance to nearest conservation site variable seems only slightly inflated in the OLS model. The SLM estimates, as distance to nearest heritage site increases by 1m, log of resale price decreases by 0.00619%, smaller than the effect suggested by OLS model (0.0163%). However, in the final SEM, for every 1m increase in distance to nearest conservation site, log of resale price decreases by approximately 0.0150%, much closer to the baseline model.

In the SLM, spatial lag variable, Rho (ρ), is positive and statistically significant, suggesting when resale prices of 100 nearest flats increase, resale price of each flat increases too, indicating adding the lag term yields a better model than OLS specification. Both spatial models have better AIC, and statistically significant Wald Statistics, suggesting they improve the OLS model, given that likelihood ratio test of SLM is also significant. In the SEM, however, Lambda (λ), which measures spatially correlated error, is small (0.0091431) and significant, suggesting spatial effects are not completely removed.

Across all models, all structural variables, including remaining lease, floor level, flat type and model have expected signs and are statistically significant at 5% level of significance, with the exception of Standard and DBSS flat model variables in the SEM model, implying they retain important roles in explaining resale flat values. By comparison, effect sizes of distance to nearest heritage site are comparably similar to other neighbourhood amenities such as proximity to nearest MRT station or park. Although not a measure of variable importance, this suggests the impact of heritage amenities on resale values in gentrified neighbourhoods should perhaps not be overstated. Contrary to initial expectations, all models suggest distance to the nearest supermarket, bus stop and carpark have no significant impact on resale values. However, the SLM suggests distance to nearest MRT station has a much smaller effect size than the OLS model. Contrary to initial OLS model, both spatial models yield an unexpected positive sign for distance to the nearest good primary school in the spatial models.

Interestingly, the town variable, indicating the neighbourhood a flat is located in, suggests statistically significant differences in log of resale price prevail across different gentrified neighbourhoods. In both OLS model and SLM, all town/neighbourhood variables are significant at 5% level of significance. Using Ang Mo Kio as reference category, on average, flats in Bukit Timah, Clementi and Marine Parade have consistently higher resale prices than those in Ang Mo Kio, while flats in Geylang have lower resale prices. A flat in Bukit Timah costs between 7.06-8.74% more than one in Ang Mo Kio, while one in Clementi costs between 1.15-1.18% more, and one in Marine Parade costs 14.2-14.7% more than a flat in Ang Mo Kio. Conversely, in the SLM or OLS, log of resale price decreases by 5.53% or 19.3% if a flat is located in Geylang.

Curiously, while Bukit Merah and Toa Payoh dummies achieve a positive sign in OLS model, this impact becomes negative in both spatial models, although the latter is insignificant in SEM. For the SEM, a flat located in Bukit Merah experiences 9.54% decrease in log of resale price relative to one in Ang Mo Kio. Interestingly, only town variables for Bukit Merah, Bukit Timah and Marine Parade remain significant in the SEM, with their impact nearly doubling relative to the OLS model. Log of resale price of a flat in Bukit Timah is 12.15% more than one in Ang Mo Kio, while for Marine Parade this is approximately 23.71%.

Table 9. *OLS model 1 results*

Variable	Coefficient	P-Value	Significance
Intercept	12.57	< 2e-16	***
Remaining Lease	0.006029	< 2e-16	***
Storey/Floor Level	0.00718	< 2e-16	***
Flat Type - 5 Room	0.6322	< 2e-16	***
Flat Type - 4 Room	0.3224	< 2e-16	***
Flat Type - 2 Room	-0.2915	< 2e-16	***
Flat Type – 1 Room	-0.4804	< 2e-16	***
Flat Model - Maisonette	0.7749	< 2e-16	***
Flat Model - Apartment	0.7815	< 2e-16	***
Flat Model - Improved	-0.05775	< 2e-16	***
Flat Model - Model A	0.05519	< 2e-16	***
Flat Model - Adjoined Flat	0.4824	< 2e-16	***
Flat Model - Simplified	-0.1352	< 2e-16	***
Flat Model – Model A Maisonette	0.2636	< 2e-16	***
Flat Model - Terrace	0.7292	< 2e-16	***
Flat Model - Standard	-0.05683	< 2e-16	***
Flat Model - DBSS	0.1009	0.000654	***
Town – Bukit Merah	0.04181	< 2e-16	***
Town – Bukit Timah	0.08744	4.44e-12	***
Town – Clementi	0.01815	0.000271	***
Town – Marine Parade	0.1470	< 2e-16	***
Town – Toa Payoh	-0.1070	< 2e-16	***
Town- Geylang	-0.1939	< 2e-16	***
Distance to Nearest Conservation Area	-0.0001627	< 2e-16	***
Distance to Nearest MRT station	-0.00008206	< 2e-16	***

Distance to Nearest Shopping Mall	-0.00007420	< 2e-16	***
Distance to Nearest Good Primary School	-0.00001177	0.026039	*
Distance to Nearest Hawker Centre	-0.0001085	< 2e-16	***
Distance to Nearest Park	-0.00006679	4.71e-09	***
	R^2	0.9142	
	Adjusted R^2	0.9138	
	F-Stat	2844	
	P(F-Stat)	< 2.2e-16	

*Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Table 10. *Spatial lag model 1 results*

Variable	Coefficient	P-Value	Significance
Intercept	4.6378	< 2e-16	***
Remaining Lease	0.006762	< 2e-16	***
Storey/Floor Level	0.0059364	< 2e-16	***
Flat Type - 5 Room	0.54484	< 2e-16	***
Flat Type - 4 Room	0.26710	< 2e-16	***
Flat Type - 2 Room	-0.32881	< 2e-16	***
Flat Type – 1 Room	-0.46384	< 2e-16	***
Flat Model - Maisonette	0.71939	< 2e-16	***
Flat Model - Apartment	0.71787	< 2e-16	***
Flat Model - Improved	-0.049279	< 2e-16	***
Flat Model - Model A	0.033405	< 2e-16	***
Flat Model - Adjoined Flat	0.4865	< 2e-16	***
Flat Model - Simplified	-0.11417	< 2e-16	***
Flat Model – Model A Maisonette	0.21679	< 2e-16	***
Flat Model - Terrace	0.73805	< 2e-16	***
Flat Model - Standard	-0.00046507	< 2e-16	***
Flat Model - DBSS	0.12399	0.000654	***
Town – Bukit Merah	-0.039392	< 2e-16	***
Town – Bukit Timah	0.070636	4.44e-12	***
Town – Clementi	0.01157	0.000271	***
Town – Marine Parade	0.14192	< 2e-16	***
Town – Toa Payoh	0.0011802	< 2e-16	***
Town- Geylang	-0.055376	< 2e-16	***
Distance to Nearest Conservation Area	-0.000061915	< 2e-16	***
Distance to Nearest MRT station	-0.00000041997	< 2e-16	***

Distance to Nearest Shopping Mall	-0.000071505	< 2e-16	***
Distance to Nearest Good Primary School	0.0000029892	0.026039	*
Distance to Nearest Hawker Centre	-0.0001085	< 2e-16	***
Distance to Nearest Park	-0.00015346	4.71e-09	***

LR Test Value: 160.63
p-value: < 2.22e-16
Wald Statistic:258.2
p-value: < 2.22e-16
Log-likelihood Ratio Test 333.8
p-value <2.22e-16
Rho: 0.0059875
p-value: <2.22e-16
AIC: -2110.8 (AIC for lm: -1952.2)

Table 11. *Spatial error model 1 results*

Variable	Coefficient	P-Value	Significance
Intercept	12.503	< 2.2e-16	***
Remaining Lease	0.0063672	< 2.2e-16	***
Storey/Floor Level	0.0056553	< 2.2e-16	***
Flat Type - 5 Room	0.54558	< 2.2e-16	***
Flat Type - 4 Room	0.26313	< 2.2e-16	***
Flat Type - 2 Room	-0.34412	< 2.2e-16	***
Flat Type – 1 Room	-0.46310	4.432e-05	***
Flat Model - Maisonette	0.73746	< 2.2e-16	***
Flat Model - Apartment	0.73140	< 2.2e-16	***
Flat Model - Improved	-0.034786	0.0034134	***
Flat Model - Model A	0.060002	3.973e-06	***
Flat Model - Adjoined Flat	0.44752	< 2.2e-16	***
Flat Model - Simplified	-0.063031	0.0286127	***
Flat Model – Model A Maisonette	0.23669	4.939e-11	***
Flat Model - Terrace	0.75506	< 2.2e-16	***
Flat Model - Standard	0.0049443	0.7473944	
Flat Model - DBSS	0.097973	0.0950792	
Town – Bukit Merah	-0.09.5422	0.0012547	***
Town – Bukit Timah	0.12149	0.0027204	***
Town – Clementi	0.058652	0.2427109	
Town – Marine Parade	0.23714	0.0026853	***
Town – Toa Payoh	-0.043193	0.5807624	
Town- Geylang	-0.011005	0.8916162	
Distance to Nearest Conservation Area	-0.00014979	1.672e-09	***
Distance to Nearest MRT station	-0.000018988	0.4325966	

Distance to Nearest Shopping Mall	-0.000074005	0.0008727	***
Distance to Nearest Good Primary School	0.000054175	0.0039232	***
Distance to Nearest Hawker Centre	-0.000025843	0.3687321	
Distance to Nearest Park	-0.00011474	0.0006007	***

LR Test Value 244.98
p-value <2.22e-16
Wald Statistic 1494.7
p-value < 2.22e-16
Lambda: 0.0091431
p-value:<2.22e-16
AIC: -2193.4 (AIC for lm: -1950.4)

4.5.3. Model 2 – Varying Effect of Proximity to Conserved Heritage Across Different Zones

Model 2 results demonstrate premium for HDB resale flats based on proximity to heritage sites declines in a consistent fashion from Zone 2 to 4. Unexpectedly, in Zone 1, as distance from the nearest heritage site increases by 1m, log of resale price decreases by 0.006126%, where this effect size is smaller in comparison to all other proximity zones. The latter decreases by 0.03976% in Zone 2, by 0.02206% in Zone 3 and 0.0159% in Zone 4, such that price effect of heritage attenuates with flats in zones situated further away from heritage sites. Although providing mixed evidence for a distance-decay relationship, this is similar to Tan and Ti's (2020) findings where price effect of built heritage is most pronounced among private properties within the 800 to 1600m radius of heritage sites, implying similar patterns prevail in the public property market. However, proximity to nearest heritage site ceases to be significant in Zone 5 (1600-2000m), where other explanatory variables such as distance to nearest good primary school better explain variation in resale prices.

Across proximity zones, however, town dummy variables are not consistently significant. Moreover, in Zones 3 and 5, no town variables were found significant. However, similar to earlier models explored, Model 2 confirms being located in Toa Payoh, Geylang, Bukit Merah negatively impacts log of resale price of a flat, while being located in Bukit Timah, Clementi, Queenstown, Marine Parade positively impacts log of resale price.

Some inconsistency in signs is observed across zones, particularly with locational variables denoting distance to nearest amenity, such as supermarket, good primary school or park, with these sign changes potentially reflecting other exogeneous influences or neighbourhood-level discrepancies which Section 5 explains.

Adjusted R-squared for all zone regressions is high, indicating they explain between 82.61% to 94.73% of variance in the dependent variable, while the statistically significant F-statistics suggest the models provide a better fit to the data than the null hypothesis.

Table 12. *Model 2 results*

	Zone 1		Zone 2		Zone 3		Zone 4		Zone 5	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Intercept	12.56	< 2e-16	12.87	< 2e-16	12.57	< 2e-16	13.11	< 2e-16	12.26	< 2e-16
Remaining Lease	5.926e-03	< 2e-16	3.682e-03	2.75e-15	6.691e-03	< 2e-16			0.0076987	< 2e-16
Storey/Floor Level	6.658e-03	< 2e-16	6.016e-03	< 2e-16	8.495e-03	< 2e-16	8.603e-03	< 2e-16	0.0089870	0.000188
Flat Type - 5 Room	0.6414	< 2e-16	0.6907	< 2e-16	0.6156	< 2e-16				
Flat Type - 4 Room	0.3137	< 2e-16	0.3265	< 2e-16	0.3351	< 2e-16	0.3281	< 2e-16	0.3806884	< 2e-16
Flat Type - 2 Room	-0.2920	< 2e-16	-0.2310	< 2e-16	-0.2693	< 2e-16				
Flat Type – 1 Room	-0.4850	< 2e-16								
Flat Model - Maisonette	0.7238	< 2e-16	0.8371	< 2e-16	0.8869	< 2e-16	0.7221	< 2e-16		
Flat Model - Apartment	0.7847	< 2e-16	0.1425	1.26e-06	0.8300	< 2e-16	0.8328	< 2e-16		
Flat Model – DBSS							0.7899	< 2e-16		
Flat Model - Improved	-0.08466	< 2e-16	-0.06323	-6.304e-02	4.68e-05	< 2e-16	0.6196	< 2e-16		
Flat Model - Model A	0.05834	3.33e-11	0.1061	3.22e-14	-0.02732	0.027427	0.3547	< 2e-16		
Flat Model - Adjoined Flat	0.2049	1.48e-11	0.3995	3.78e-10	0.7318	< 2e-16	0.8498	< 2e-16	0.7774235	0.00505
Flat Model - Simplified	-0.1128	2.36e-15	0.05001	9.40e-10						
Flat Model – Model A Maisonette	0.2434	< 2e-16	0.1277	0.014803						
Flat Model - Terrace	0.7364	< 2e-16								

Flat Model - Standard	-0.08767	< 2e-16	-0.08449	8.08e-06			0.6317	< 2e-16		
Town – Bukit Merah			-0.1076	0.000309						
Town – Bukit Timah	0.1186	< 2e-16								
Town – Clementi			0.07890	1.25e-08			0.08968	2.33e-10		
Town – Marine Parade	0.1751	< 2e-16								
Town – Queenstown	0.05956	< 2e-16								
Town- Geylang	-0.1494	< 2e-16	-0.4110	< 2e-16						
Town – Toa Payoh	-0.06596	< 2e-16	-0.1057	< 2e-16						
Distance to Nearest Conservation Area	-6.126e-05	0.00724	-3.976e-04	1.13e-15	-2.206e-04	< 2e-16	-1.590e-04	2.30e-15		
Distance to Nearest MRT station	-4.449e-05	0.00237	-2.486e-04	< 2e-16			-1.952e-04	< 2e-16		
Distance to Nearest Bus Stop							-4.421e-04	0.00038		
Distance to Nearest Shopping Mall	-5.652e-05	1.72e-05			-1.720e-04	< 2e-16				
Distance to Nearest Good Primary School					4.829e-05	3.15e-07	-4.596e-05	0.02719	0.0002061	8.94e-07
Distance to Nearest Supermarket	1.995e-04	8.08e-15	-1.204e-04	0.016534						
Distance to Nearest Hawker Centre	-1.900e-04	< 2e-16			-1.717e-04	7.96e-11				
Distance to Nearest Carpark					-2.917e-04	0.000625	-3.658e-04	0.00197		
Distance to Nearest Park	-2.446e-04	< 2e-16			5.725e-05	0.025106	1.803e-04	2.90e-07		
R-squared	0.9192		0.9485		0.919		0.8913		0.8355	

Adjusted R-squared	0.9187	0.9473	0.9181	0.8896	0.8261
F-Stat	1781	843.6	999.3	527.4	89.37
p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

4.5.4. Regression Model Diagnostics

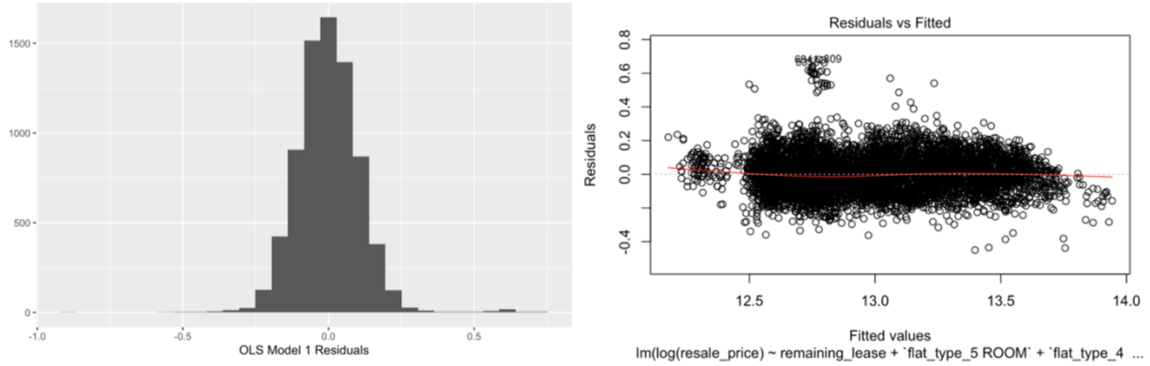
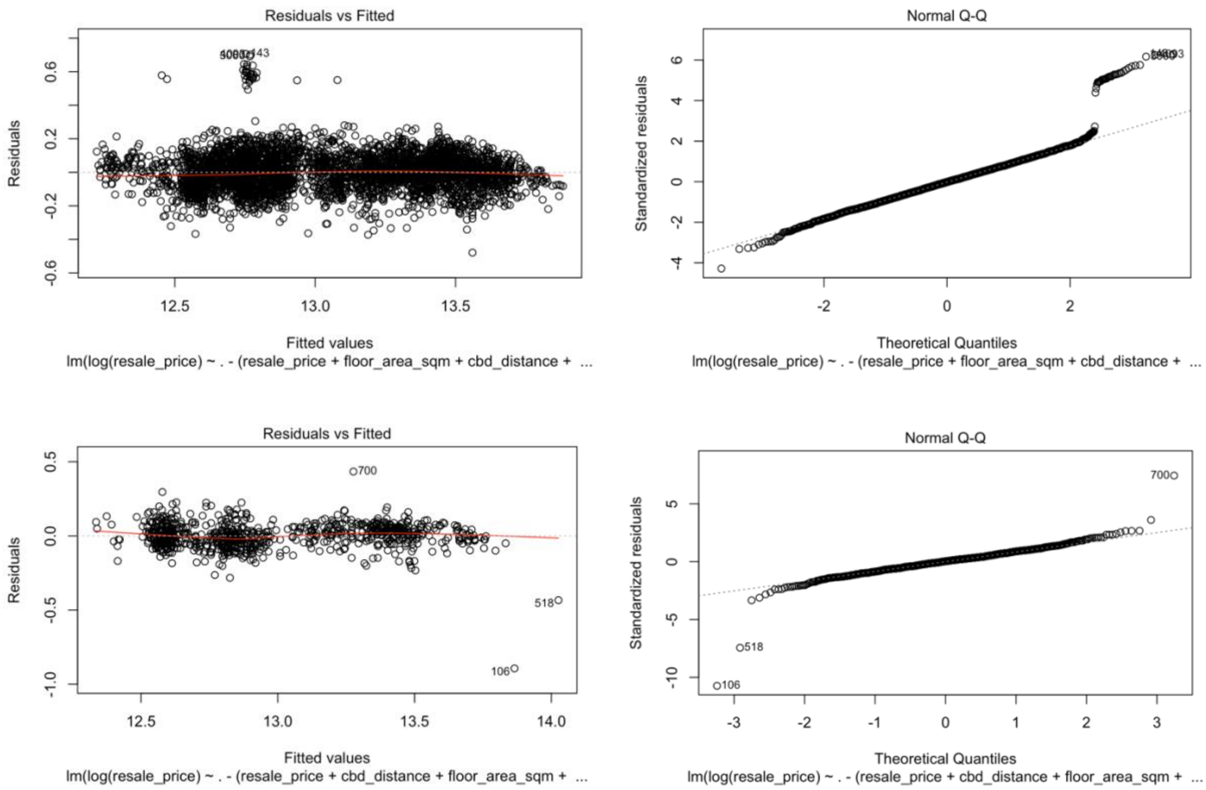


Figure 30. Model 1 diagnostics

Residuals in OLS Model 1 are normally distributed, with no apparent homoscedasticity observed in residuals, demonstrating assumptions for linear regression are met.



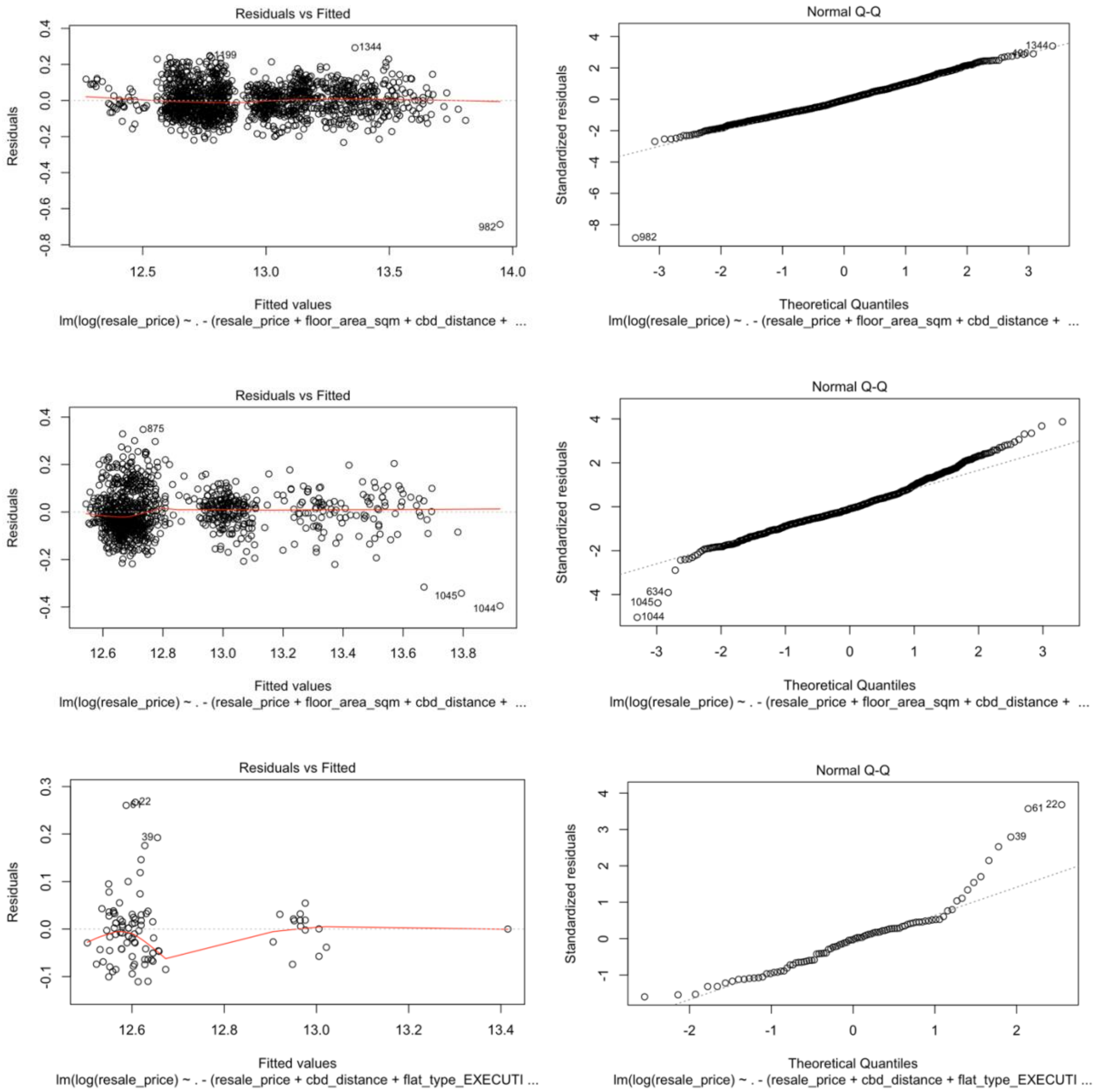


Figure 31. Model 2 Zone 1-5 diagnostics

While normal Q-Q plots indicate residuals are largely normally distributed in Zones 1-4, this assumption is violated in Zone 5, potentially undermining F-stat for model fit, while rendering p-values and confidence intervals inaccurate. This consequence likewise applies to Zone 4-5 where residuals vs fit plots demonstrate heteroskedasticity, violating assumption of constant variance.

5. Discussion

5.1. Contextualising ‘Gentrification’ to Singapore: Singapore’s Emerging Geography of Gentrification

The nature and spatial patterning of gentrification in Singaporean neighbourhoods indicated by the typology of socio-economic trajectories raises potential discontinuities with and problematises wholesale applicability of conventional understandings underpinning gentrification literature. First, while gentrification is commonly defined as transformation of ‘working-class’, derelict and even socio-economically marginal neighbourhoods (Atkinson, 2004; Lees et al, 2008), not all ‘gentrified’ neighbourhoods in Singapore have been previously stigmatised, struggling or lagging behind on socio-economic indicators. Rather, variation across neighbourhood clusters is not dramatic, with unemployment levels remaining similar across all years. Moreover, ascent of already affluent neighbourhoods into urbanised, elite areas appears to go against the grain of classical gentrification definitions.

Rather than completely abandon the term ‘gentrification’ in Singapore’s context, it suggests these neighbourhood trajectories need to be interpreted against the larger backdrop of Singapore’s urban planning history and use of cultural heritage as a gentrification tool (Tay and Coca-Stefaniak, 2010). Spatiality of Singapore’s ‘gentrified’ neighbourhoods, or planning areas, (Ang Mo Kio, Clementi, Queenstown, Bukit Merah, Geylang, Kallang and Toa Payoh) is mirrored by the existing distribution of mature, ageing housing estates, where amidst increasing presence of a more youthful, highly-educated, white-collar population, there is simultaneously a substantial proportion of elderly aged 65 and above (Hu and Caballero, 2016). Yet, this apparent paradox is not unexpected, and can be further attributed to the centrality of heritage conservation in prompting entry of the ‘creative-class’ into these mature estates, resulting in socio-economic, demographic shifts characteristic of gentrification (Ley, 2003). Dialectical interplay between commercial and residential gentrification through conservation of cultural, architectural heritage may explain this, where Chang (2016) observes rejuvenation of historic districts such as Little India is often preceded by entry of diverse arts and cultural businesses, eateries and hotels. Similarly, in Bukit Merah, the conserved Tiong Bahru estate, Singapore's oldest planned housing estate with many elderly residents, contains numerous blocks of flats with pre-war architectural styles (URA, 2019), has similarly witnessed an influx of hipster cafes, F&B establishments and local artists capitalising on its art deco architecture (Caballero, 2016), attracting expatriates and Singaporeans seeking rustic neighbourhoods with unique identities (Ting, 2015). Contrary to Chang's (2016) framing of gentrification in Singapore as predominantly commercial, effects of residential and commercial gentrification may not be so sharply distinct in Singapore, given that spatial patterning of gentrified neighbourhoods is closely tied to geographical loci of heritage conservation housing multiple commercial and residential uses.

Similar to Yuen (2006), these findings expand Wong's (2005) initial understanding of residential gentrification as a process spatialised solely within luxury private residences within Singapore's waterfront CBD. Rather, 'downtown gentrifiers' are increasingly found in valorised, culturally-rich, aestheticized neighbourhoods with vernacular housing (Waley, 2016). Although URA's Conservation Master Plan 1985 initially highlighted 6 conservation areas consisting of centrally-located cultural, ethnic enclaves and Civic District, it has since expanded to conserve over 7,000 buildings, including historic adjacent neighbourhoods surrounding the city's CBD (URA, 2020). This potentially contributes to geographical spreading of gentrification pressures across housing estates in close proximity to heritage sites (Eckerd, 2011). Thus, Singapore's neighbourhood gentrification is not solely confined to the downtown core, but has extended its reach to public housing estates through other historically valuable districts on the fringes of the city's commercial centre.

Responding to legitimate academic concerns over displacement of lower-income, socio-economically vulnerable households (Marcuse, 1986; Atkinson, 2004) or elderly residents (Hu and Cabarello, 2016:7), upgrading of affluent neighbourhoods to elite which simultaneously house sizeable elderly populations from 2000 to 2015, with largest proportions of private condominiums and landed estates (Bukit Timah, Tanglin, Novena, Marine Parade) suggest displacement of lower-income and elderly residents in Singapore are not necessarily taken-for-granted outcomes of gentrification (Shin et al, 2015). Rather, these neighbourhoods provide some support for Pow's (2009) suggestion that 'new-build' gentrification, which Moore (2013) argues is widely characteristic of East Asian gentrification, is emerging through 'condominiumisation of housing landscapes in Singapore', minimising systemic displacement where newcomers take over residences of previous occupants (Ley and Teo, 2004).

Nonetheless, these findings highlight imperative for existing urban policy in Singapore to pay more attention to mitigating these costs arising from conservation-induced gentrification in gentrified neighbourhoods. While racialised politics are not necessarily a prevalent source of tension in Singapore's gentrified neighbourhoods due to state-engineered ethnic-mixing through imposed racial quotas in public housing estates (Sin, 2002), the subtly increasing polarisation in terms of age, occupation and income indicated by neighbourhood trajectories highlight need for intentional creation of socially-inclusive public spaces to nurture common ground between old and new residents (Hu and Caballero, 2016) and facilitate continued mixing among socio-economically heterogeneous classes (Goh, 2001).

5.1.1. Limitations

However, the classification is constrained by several limitations. Firstly, the 'neighbourhood' level defined in this paper has been the larger planning area level, due to paucity of census data at smaller sub-zone divisions, which potentially obscures patterns of neighbourhood change emerging at a finer spatial resolution. Thus, the neighbourhood typology presented here is not immune to the MAUP outlined earlier. Moore (2013) further argues, gentrification in Asia may not necessarily occur at a wider 'neighbourhood' level, but could be at block-level. Despite identification of an entire planning area as gentrified or gentrifying, such effects may in reality be driven by pockets of smaller neighbourhoods or housing estates within planning areas where gentrification characteristics are most prevalent.

Secondly, subject to data availability, input variables used for neighbourhood classification could expand to include median home values (initially excluded as data is not publicly available for those preceding 2007), the extent of heritage designation within a neighbourhood (Coulson and Leichenko, 2003) and proportion of a planning area's population working blue-collar jobs. Additionally, while the classification may lend limited insight into the dwelling characteristics of various neighbourhood, it is unable to provide more comprehensive exploration of well-documented 'new-build gentrification' in Singapore and its attendant processes.

5.2. Impact of Built Heritage Conservation on HDB Resale Flat Prices in Gentrified Neighbourhoods

Several theoretical and policy implications follow from regression results. Firstly, consistent significant positive impact of proximity to built heritage sites on resale prices confirm existence of a premium associated with living in the vicinity of designated heritage sites within gentrified neighbourhoods, even after controlling for spatial autocorrelation. This suggests residential location choice in such neighbourhoods may not be merely motivated by pragmatic considerations, but also aesthetic and cultural preferences reflected in consumers' implicit willingness to pay for such heritage goods (Belcher and Chisholm, 2018). In tandem with the neighbourhood classification, this reflects ability of upper and middle-classes to capitalise on and profit from higher house prices by investing in these public properties (Smith and LeFaivre, 1984), by regarding heritage designations as a preceding indication of neighbourhood upgrading which simultaneously retains the area's cultural and historical essence while expectantly boosts property values both presently and in the future, with Tan and Ti (2020) finding that resale prices of homes in the vicinity of conservation sites appreciate during the year of heritage site gazetting and three years after.

Second, some evidence of a distance-decay effect in proximity to nearest heritage site on resale flat prices illustrates influence of spatial effects in mediating property price premiums arising from conserved heritage. Across gentrified neighbourhoods, not all homeowners benefit homogeneously from the premium accrued due to heritage conservation. Moreover, in Zone 1, the positive impact of proximity is unexpectedly smaller than that of Zones 2-4, raising questions about the inconsistency of the 'distance-decay' effect of proximity to conserved heritage on housing resale prices. To this end, Tan and To (2020:17) suggest, impact of heritage on housing prices is "complex and location-specific", as flats located closer to heritage sites tend to be more proximate to the city centre where conservation sites are concentrated, such that homeowners living in Zones 1 to 4 may have varying opinions on whether proximity to a heritage site necessarily constitutes an amenity depending on specific spatial features of the particular neighbourhood not captured through the models. This explanation could be extended to the inconsistent signs demonstrated by locational variables across proximity zones, suggesting across homeowners, there may not necessarily be an easy consensus on whether proximity to various points of interest such as supermarkets, primary schools or parks is regarded amenity or disamenity.

Third, unexpectedly, the regression results suggest flats in some particular gentrified neighbourhoods, such as Bukit Timah, Clementi, Queenstown and Marine Parade, are perceived more favourably by homebuyers over those located in Geylang, Bukit Merah,Toa Payoh. This might be attributed to the functionality of Singapore's different neighbourhood districts (Mo, 2014), where house premiums are attached to premier residential zones close to the city's commercial centre and those adjacent to them. Conversely, disamenity is associated with planning areas exhibiting predominance of light industrial business, 'taboo' trades, or relatively underdeveloped neighbourhoods in the north, west and northeast regions. For example, Geylang planning area, formerly infamous for housing a seedy, 'red-light district', although now remade through various cultural bazaars and community events, may still be perceived more negatively relative to other neighbourhoods. Moreover, Han (2005) identifies the presence of 'property-value' clusters in Singapore, suggesting a high-value condominium cluster is found in Singapore's central area, while low-value cluster found in Singapore's northeast area, adjacent to Toa Payoh and Geylang. Given that private residences are likely have spill-over effects on surrounding public flats (Bardhan et al, 2003), amalgamation of heritage conservation and newly-built condominiums which contribute to the spatial patterning of neighbourhood gentrification in Singapore, could further result in differentiated premiums across gentrified towns.

Finally, from a policy perspective, despite URA's predominantly market-led approach in promoting quality physical restoration of historic structures and adaptive reuse, it has acknowledged exigency for a more community-driven conservation strategy sensitive to the needs of local residents (CLC, 2017). That considerable amenity value is attributed by Singaporean homeowners to conserved heritage sites in housing markets as quantified in this paper justifies a favourable assessment of conservation policies, with the possibilities of such values reflecting great demand for careful preservation of local place authenticity, cultural identities more than just physical facades, amidst prevailing tensions between enhancing the "economic potential and viability of a conserved district versus its conservation value" (CLC, 2019:112). As Tay and Coca-Stefaniak (2010) suggest, Singapore's urban revitalisation strategies involving heritage conservation could foster greater public stakeholder engagement and collaboration in anticipation of potential alterations to neighbourhood character induced by gentrification.

5.2.1. Limitations

However, several important limitations remain. Firstly, the regression models have not examined property transactions in other non-gentrifying neighbourhoods as a control group to compare the impact of heritage on resale prices. Moreover, temporal escalation in individual property values characteristic of gentrified neighbourhoods, along with lags in property appreciation potentially resulting from heritage conservation, has not been considered in this paper, as this is itself limited by data availability. Limiting the study period to 2014 to 2016, a period of relative stability in the public property market inadvertently restricts insight into temporal trends of resale values. The paper's scope is limited to eliciting price effects of heritage areas in gentrified neighbourhoods, instead of estimating how much of a property's appreciation over time is attributed to heritage conservation. Therefore, the results have not demonstrated, and should not be taken as evidence of a causal relationship between *increasing* resale value and gentrification pressures from heritage conservation.

Secondly, results are not immune from endogeneity problems arising from omitted variable bias. Other explanatory factors unaccounted for, such as overlap between political boundaries with planning area boundaries determining whether neighbourhood falls into an politically-incumbent or opposition ward may have impacts on resale prices (Lehner, 2011). This could affect likelihood of a neighbourhood experiencing upgrading and renewal schemes (Sue and Wong, 2010). While proximity to CBD was excluded due to extremely high VIF in all models, concentration of heritage sites close to the city centre could make it difficult to interpret price effects of conserved heritage on resale prices in isolation from the amenity derived from a flat being located close to the city centre.

Thirdly, Model 2 residuals are not all normally-distributed, undermining reliability of significance tests. To address this, future modifications could incorporate distance bands as ordinal variables into Model 1 instead.

Finally, while models regard all built heritage sites as having a homogeneous price effect, decomposing their impact by type and nature of heritage could instead paint a more nuanced, diverse picture of the impact of heritage sites on residential resale prices.

6. Conclusion

Responding to the palpable dearth of quantitative studies of heritage-induced gentrification situated in an East Asian context like Singapore's, this study has synthesized neighbourhood change and the impact of heritage on resale house prices into an analytical framework so as to enhance existing understandings of the spatiality of gentrification in relation to heritage sites, and how such spatial effects may be captured through property values. This understanding is crucial to alleviating the tensions between policy intent behind the preservation of cultural and architectural heritage, development risk, and increasing awareness of the potential socio-economic pitfalls of heritage-led urban gentrification in the absence of adequate social mixing and integration policies.

Using a combination of clustering techniques and spatial regression analysis, the paper identified a novel typology of neighbourhood trajectories in Singapore, where gentrified neighbourhoods are located around and close to the city centre. It demonstrated, within these gentrified neighbourhoods, proximity to heritage sites generally has a small, positive and significant impact on house prices, although the distance decay effect holds only from distances of 400m to 1600m.

However, it is acknowledged future work and improvements could be undertaken in several avenues. Firstly, as noted earlier, inclusion of a control group consisting of neighbourhoods with trajectories not demonstrating gentrification or upward ascent could facilitate stronger conclusions concerning pronounced price effects of heritage on resale flat prices in gentrified housing estates. Secondly, instead of using Euclidean distance to nearest amenities, other cost distance measures such as travel time could be employed to better capture complex spatial relationships between residential properties with various points of interest mediated through modes of transport (Cao et al, 2018). Moreover, despite computational constraints faced in this paper, future work could expand the time period of resale transactions to those before 2014, while including a time-series component in the model specification, to derive more comprehensive insight into temporal price effects of heritage on house prices.

Furthermore, this paper raises questions concerning the diversity of sequences of neighbourhood socio-economic change in Singapore, suggesting future expansion of the classification algorithms to include input variables enabling a wider study of neighbourhood classes and change typologies instead of searching only for 'gentrification trends', may provide fertile ground for deeper understanding of neighbourhood differentiation in Singapore. Given that causes of gentrification are diverse (Hochstenbach and van Gent, 2015), although this paper identifies heritage conservation as a predominant force, future work does not preclude an examination of other potential sources of gentrification in Singapore. Additionally, the results ultimately only lend insight into public residential resale market, and not into price effects of heritage amenities on *private properties* in gentrified areas. In close relation, although the effects of new-build gentrification arising from the construction of new private condominiums is beyond the paper's scope, a potential area of future research could be examining effects of new condominiums as a gentrification source on surrounding public flat resale prices.

Finally, in providing a quantitative approach to illuminating impacts of built heritage on house prices in gentrified areas, this paper is neither attempting to depoliticise the question of gentrification nor potentially entrench the value and amenity of cultural heritage in a purely economistic discourse (Maer, 2014). Rather, it acknowledges immense intangible welfare benefits arising from cultural heritage – social, psychological, spiritual and artistic values (Riganti and Nijkamp, 2004) – that may not necessarily be captured in this study, but which remain no less important.

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