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Innovative measurement of spatial segregation: Comparative evidence from Hong Kong and San Francisco

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ABSTRACT

The spatial distribution of households of different socioeconomic groups in urban areas has drawn longstanding attention from scholars because residential location patterns have important impacts on social outcomes and the economic efficiency of cities. Recent comparative work on this topic has yielded some insight into the causes and consequences of segregation patterns, but much of this comparison is indirect. An explicitly spatial version of the entropy index has recently been developed that facilitates comparison, as it allows for the disaggregation of segregation levels by scale and income (Reardon and O'Sullivan, 2004; Reardon, 2009; Reardon and Bischoff, 2011). This paper applies these new measurement techniques to two metropolises; Hong Kong and San Francisco. Although overall segregation levels are similar, the shape of the segregation profile across geographic scales and the income distribution is quite different. The paper also includes a script for calculating spatial ordinal segregation indices in ArcGIS.

1. Introduction

As access to geographic data increases, so has international research on segregation, including comparative work (Nightengale, 2012; Maloutas and Fujita, 2012). Yet, too little of this new comparative work in segregation provides direct comparison between cities in different countries. One notable exception is Harsman and Quigley (1995), which compares segregation patterns in San Francisco and Stockholm and assesses the extent to which racial and ethnic segregation is conditional upon housing stock and incomes. Differences between data reporting across countries often complicate comparison, but so do standard measures of the phenomenon, as they often report only one number as the segregation level. Fortunately, new measures have been created that disaggregate segregation across spatial scales and across the income distribution (Reardon and O'Sullivan, 2004; Reardon, 2009; Reardon and Bischoff, 2011). These spatial, ordinal indices have thus far only been applied to cities in the United States.

This paper compares segregation levels and patterns in the San Francisco Metropolitan Statistical Area (MSA) and Hong Kong. Hong Kong has a larger population size, but both metropolitan areas share a similar, land constrained geography, with ample mountains and water throughout. Although San Francisco is one of the densest cities in the United States, Hong Kong is one of the densest cities in the world. With slightly more than 1000 km^2 of land, its urban landscape is characterized by high-rise residential buildings, many of which reach 50 floors, even in areas far from the city center. The prevalence of large residential buildings are likely to affect segregation patterns, concentrating housing units of a similar price and thus households with similar purchasing power on one parcel of land. Hong Kong also has a highly unequal income distribution; data from the most recent census (2006) yielded a Gini coefficient of 0.53 in 2006 (Census and Statistics Department, 2007b), higher than that of most US cities, which have an average of 0.42 (Reardon and Bischoff, 2011).

The spatial dimension of economic inequality in the two cities is compared using recently developed measurement techniques to analyze segregation at different spatial scales and across the income distribution (Reardon and O'Sullivan, 2004; Reardon, 2009; Reardon and Bischoff, 2011). We analyze small area census data with income reported over more than 10 categories over a 15 year period in Hong Kong and compare with the same calculations for the San Francisco MSA in 2000. Hong Kong has a similar overall level of segregation as the metropolitan area of San Francisco and the average city in the United States. However, differences in the way households are segregated across space and the income distribution are substantial. Segregation levels in Hong Kong drop rapidly as the scale increases; a pattern that likely results from its high density but also reflects the fragmentation of urban space in Hong Kong.

The difference in segregation levels across the income distribution is less easily explained. When calculated using a rank-order index, segregation levels are found to increase consistently with income in Hong Kong. Households in the 90th percentile of the income distribution are roughly 2.5 times more segregated than households in

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the 10th percentile. This pattern is in sharp contrast to those found in the United States, where segregation levels tend to form a U-shape when mapped across the income distribution and low-income households experience similarly high levels of segregation as high-income households (Reardon and Bischoff, 2011).

After a brief review of the literature on socioeconomic segregation and recent advances in its measurement, we introduce the urban context of Hong Kong. Then, we present the geographic and census data from Hong Kong and compare them with equivalent data from San Francisco. Finally, segregation levels and patterns in the two cities are analyzed.

2. Spatial socioeconomic segregation

2.1. General approaches the phenomenon

Scholars from the fields of sociology (Duncan and Duncan, 1955; Park, 1957; Wilson, 1987; Massey and Denton, 1993) and urban economics (Tiebout, 1956; Schelling, 1978) have studied the uneven distribution of different groups within cities for decades. Sociologists have tended to focus on the structural forces that separate people of different races or income groups, including racial discrimination (Galster and Godfrey, 2005), public housing policy (Massey and Kanaiaupuni, 1993), patterns of urban immigration and assimilation (Park, 1957), and localized land-use controls (Jargowsky, 2002).

Urban economists, on the other hand, generally emphasize the way individual decisions influence where people live (Tiebout, 1956). One important contribution from the field is the theoretical insight that residential location is determined through a competitive bidding process for land for housing, and thus land markets play an important role in the distribution of different socioeconomic groups (Mills and Hamilton, 1994). As cities grow, land values become increasingly differentiated due to increases in commuting costs and increasing differences in the mix of public services and natural amenities in different locations. This leads to a greater differentiation of residential neighborhoods, although the process is partially endogenous. The connection between this line of reasoning and structural study of racial segregation was emphasized in the work by Harsman and Quigley (1995), who found that a large share of racial segregation could be explained by differences in income between racial groups.

Another avenue of research has attempted to ascertain the determinants of segregation more generally by using statistical analysis across a large number of cities within a country (Telles, 1995; Pendall and Carruthers, 2003; Monkkonen, 2012). These studies assess the relationship of a number of factors with levels of segregation at the city level, using statistical controls to estimate the relative impact of each. In Mexico, for example, cities with more housing finance are more segregated (Monkkonen, 2012). Population density, for example was found to have a quadratic relationship with segregation in the United States; cities with very low and very high population densities had higher levels of segregation (Pendall and Carruthers, 2003). Bigger cities are consistently found to be more segregated, presumably because more competitive land markets lead to greater neighborhood differentiation.

2.2. Advances in measurement

Any analysis of segregation is only as good as the measurement of the phenomenon, which has been an active research area among sociologists, geographers, and other social scientists since the 1950s (Duncan and Duncan, 1955; Taeuber and Taeuber, 1965). This paper takes advantage of recent advances in the measurement of two different aspects of socioeconomic separation within cities that build on a work dating back to the 1970s and 1980s (Morgan, 1975; Jakubs, 1981). The first aspect is the measurement of segregation of multiple, ordinal groups, specifically households of different incomes (Meng et al., 2006; Reardon and Bischoff, 2011) and the second is an explicit consideration of the spatial relationship of households of different groups across a city (Reardon and O'Sullivan, 2004; Wong, 2005).

This literature review focuses on the measurement approaches used in the present analysis. A more complete review of the literature on the measurement spatial and ordinal segregation can be found in Feitosa et al. (2007). The chief segregation index employed in the analysis of Hong Kong and San Francisco is the spatial rank-order information theory index (Reardon and Bischoff, 2011), which allows for explicit consideration of geographic scale in measuring segregation, as well as analysis of socioeconomic segregation across the income distribution. Although this index is not unique in these two features, it has been widely applied in the United States and thus a number of cities' values are available for reference.

The rank-order index is based on Theil's information theory index, or the entropy index (Theil, 1972), which essentially measures the difference between the heterogeneity of the city for a given variable and a weighted average of the heterogeneity calculated for each sub-unit of a city. Detailed formulas for the indices used in this paper, the multi-group index – the ordinal index, and the rank-order index – can be found in Appendix A and their spatial counterparts in Appendix B.

The first step in creating the spatial rank-order index was the development of a multi-group index of segregation, as traditional measures such as the dissimilarity index allowed for measurement of the separation between two groups only (Reardon and Firebaugh, 2002; Meng et al., 2006). The deficiency of the multi-group index for measuring socioeconomic segregation or the separation of different income groups, however, is that it fails to capture the ordinal nature of the data. Conceptually, the difference between a low-income household and a high-income household is greater than the difference between a low-income household and a middle-income household. One way[1] to adapt the entropy measure to ordinal data by using cumulative categories of income groups when calculating the index (Reardon, 2009). The main limitation of this approach is that its value will be influenced to some extent by the way in which income data are categorized. There can be abrupt jumps in the distribution of income when reported as categories, when in reality the distribution is generally smooth.

When income data is divided into a larger number of categories the measure is more precise. The rank-order entropy index bases its calculation on an estimated income distribution using the values of 2-group entropy indices calculated for each cumulative category of income (Reardon et al., 2006; Reardon and Bischoff, 2011). Rather than taking a weighted average of these measures, as in a standard ordinal index, a polynomial function is estimated based on the curve of segregation values across the income distribution. The index value is then calculated based on this curve. In addition to the greater precision, the method allows researchers to easily visualize segregation levels across the income distribution. A graphical illustration is presented in Fig. 5A and B below.

The challenges of accurately capturing the spatial dimension of segregation originally led Massey and Denton (1988), in a classification of the large number of indices that had emerged by the 1980s, to describe three spatial dimensions of segregation – evenness, exposure, and clustering. These three dimensions actually described one so-called super dimension, separation, and the reason for three separate measures was the inadequacy of the techniques themselves (Reardon and O'Sullivan, 2004). In part, a reliance on census tract data led to two basic approaches to measuring the spatial separation of groups: a non-spatial measurement of their distribution across tracts (the evenness or exposure component) and a spatial measure of adjacent tracts similarity (the clustering component).

[1] There are a variety of other ways to measure income segregation, such as those based on income variance (Kremer and Maskin, 1996; Davidoff, 2005). Although these indexes will be highly correlated, the rank-order index is preferable for comparative work as it measures segregation independently of the income distribution and thus inequality.

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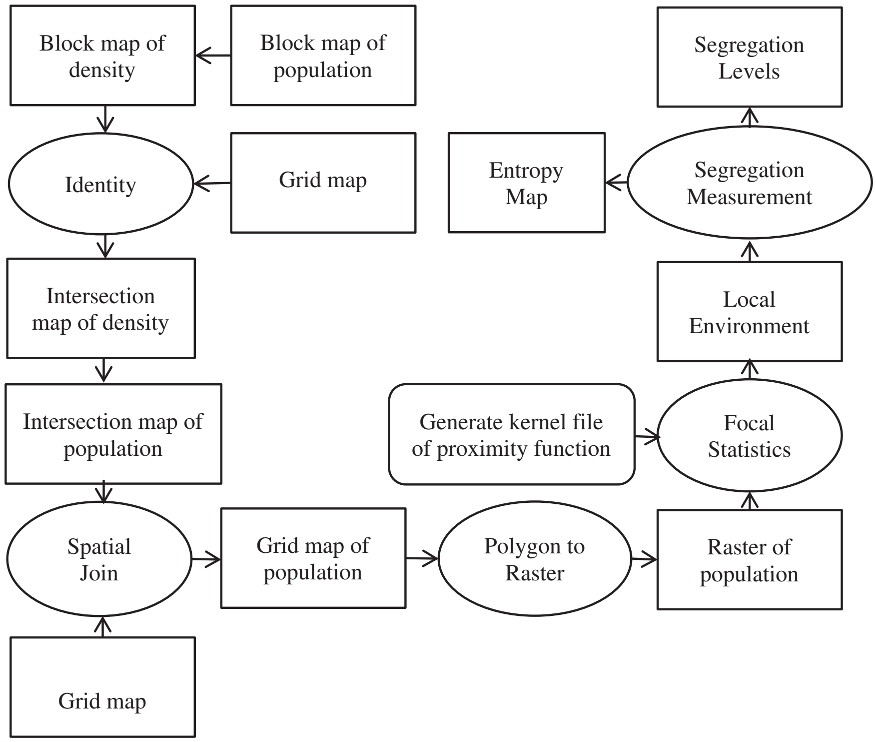

Fig. 1. Workflow of the spatial segregation geoprocessor.

Recently developed measures effectively combine the dimensions of evenness and clustering mentioned previously by calculating values at varying geographic scales (Wong, 2005; Reardon and O'Sullivan, 2004; Reardon et al., 2008; Lee et al., 2008; Feitosa et al., 2007). The conceptual innovation for these measures is to start from measuring segregation for "local environments" of different sizes for a large number of points across a city. Local environments can be thought of as neighborhoods, as they are areas that surround a given point. Ideally, these points would be households and thus segregation would be measured at different neighborhood sizes around each household. In practice, data is generally only available for small geographic areas such as street blocks or street block groups, thus local environments can be defined as aggregations of these small areas as in Wong (2005) or as in the present research, by using grid cells, which are overlain on these small area data and then recombined into circular areas of a specified size (Reardon and O'Sullivan, 2004).

In using the grid cell approach, we make the assumption that households are evenly distributed within small areas and the characteristics of the population in a grid cell are estimated according to its proportion of the small area. If a grid cell spans two small areas, the grid is split by the polylines of the small area boundary and the populations of the parts are combined. In the process of conversion to grid cells, we maintain the city's total population thus decimal values are unavoidably employed. It is clear that the two approaches have advantages and disadvantages. By using the grid cell approach, a consistent geographic scale of analysis is obtained at the expense of the assumption about the distribution of households within small areas. The inaccuracy this introduces depends on the boundaries of the original data source. It could also introduce a false sense of precision if small grids are overlain on large census tracts.

Measuring segregation at different sizes of local environment allows for comparison of segregation at larger and smaller scales, providing insight into the scale of segregation in a city. In fact, the common census tract or block group measures of segregation can be thought of as one specific spatial scale of segregation, albeit with irregular sizes across the city (Reardon and O'Sullivan, 2004). The spatial measures calculated using the technique of different sizes of local environments simply makes the scale analysis more systematic, but should always recognize the limitations of the underlying data.

In order to implement the spatial measures of segregation, we created a Spatial Segregation Geoprocessor (SSG) for this study using Python under the ArcGIS platform, automating the calculation process by combining modules from ArcObjects and calculating indices in the Python environment. Fig. 1 shows the steps of the SSG.[2] The rectangles represent data/input/output while ellipses are used to indicate processor/modules. Note that 'Identify', 'Spatial Join' and 'Focal Statistics' are built-in components of ArcGIS, and can be easily accessed from ArcToolbox.

After generating and overlaying a grid map of 50 m cells on the census map, we use a 'Spatial Join' to produce a grid map of population. Next, the grid map of population is converted from shapefile to raster format. We define the local environment with the module of 'Focal Statistics' using a distance decay function. Any function can be employed; in this case we follow Reardon et al. (2008) and use a biweight kernel function, which is less steeply sloped than a standard inverse distance function thus placing greater importance on nearby cells. After defining the local environment, we calculate different measures of segregation in Python. The module reports the computed segregation levels and entropy maps.

In the case of the rank-order index, values that indicate segregation from the rest of the population are calculated for every *cumulative* income category. Then, parameter estimates for the curve of segregation values at different points along the income distribution are generated through a polynomial regression carried out in a separate statistical package *ex post*. The calculation of the final value of the rank-order

[2] The Python script is available as supplementary material online.

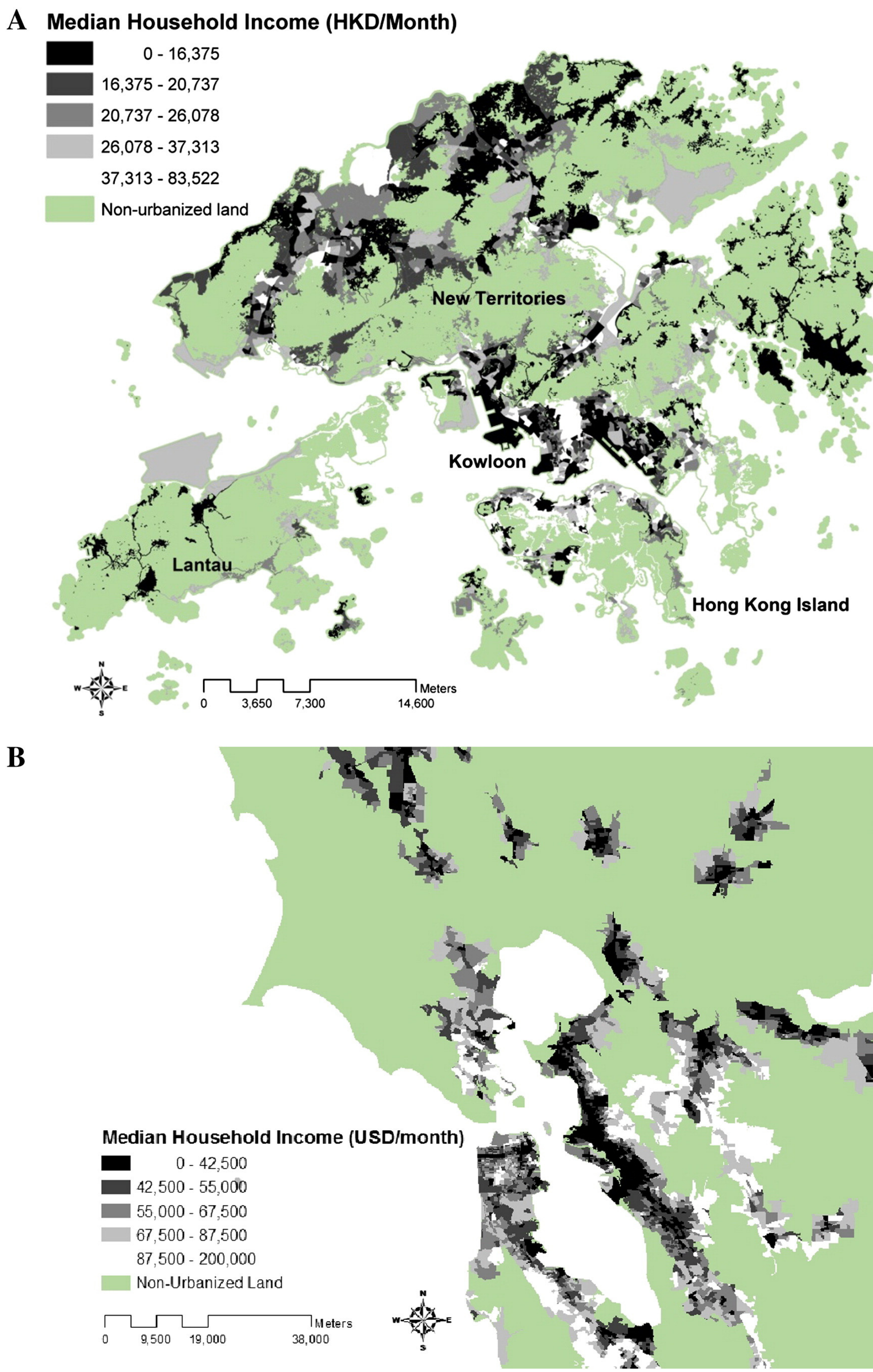

Fig. 2. A. Map of Hong Kong, Neighborhood Median Household Income, 2006. Source: Authors with Census and Statistics Department (2007a). B. Map of Hong Kong, Neighborhood Median Household Income, 2006. Source: Authors with Census and Statistics Department (2007a).

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index, which can be thought of as the average value of the curve, is then calculated using the final formula found in Appendix A, Eq. (14).

3. The two metropolitan contexts

3.1. Geography and recent changes in the economic geography of Hong Kong

A combination of natural constraints, including mountains and islands, and strict regulatory control of urban development in Hong Kong have contributed to the scattered pockets of high-density urban development across the territory. Fig. 2 is a map of Hong Kong showing the large amount of undeveloped land in the city (roughly 80% of the territory) and the peninsula and island geography of the central urban area. The map also presents the median income of the city's neighborhoods in 2006. Although there are a few pockets of high-income neighborhoods scattered across the territory, the majority are found clustered on the southern side of Hong Kong Island and in the northern part of the Kowloon Peninsula.

Fig. 2B shows a similar map for the metropolitan area of San Francisco. The distribution of high- and low-income neighborhoods is quite different. The well-documented pattern of rich, low-density suburbs and low-income, high-density central areas is evident, especially in the East Bay cities of Oakland and Hayward. The city of San Francisco itself has a larger number of high-income neighborhoods than other centrally located areas.

Hong Kong experienced a major political change in 1997, when it returned to China,[3] but the city also underwent two major transitions during the end of the 20th century; a shift from a manufacturing-dominated economy to services and a rapid expansion of the population into a peri-urban region to the north of the city known as the New Territories (Sui, 1995). The impacts of economic changes are more straightforward than those in population structure. The shift in the economy from manufacturing to producer and financial services led to an overall increase in GDP and average incomes. Notwithstanding the increase in median incomes over recent decades and a drop in the share of the population in the low-income category, income inequality actually *increased* during this time period. The Gini has grown regardless of the method used to calculate it (Census and Statistics Department, 2007b; Lui, 2011). Using household incomes, we estimate that it increased from 0.44 in 1986 to 0.49 in 2006 (Census and Statistics Department, 1986, 2006), an 11% increase.[4]

The impact of population decentralization into the New Territories on the overall socio-spatial structure of Hong Kong is less clear. Several studies have described trends toward suburbanization, residential movement, and the development of new towns (Sui, 1995; Lui and Suen, 2010). Scholars have argued that high income inequality is not reflected in spatial segregation (Forrest et al., 2004); however, this is based on an analysis conducted at what in Hong Kong is a large geographic scale. Tertiary Planning Units (TPUs) contain roughly 30,000 people, six times more than census tracts in the United States, the most commonly used geographical unit of analysis.

Nonetheless, the importance of scale is not lost on Forrest, La Grange, and Yip, who have explored the meaning and importance of neighborhood in the high-density Hong Kong context in previous work (2002). They found that in many cases, interviewees had a strong connection to their neighborhoods, and that these neighborhoods were often defined as relatively small areas. For example, several respondents mentioned their residential estate,[5] Tai Koo Shing, which covers roughly 2.1 km^2, and one respondent said "from Centre Street to Water Street.", a distance of about 300 m (Forrest et al., 2002: 225–226).

Reardon et al. (2008) proposed that a circle with a radius of 500 m – a comfortable walking distance – is an appropriate size for measuring a neighborhood in the United States. They began their analysis of segregation at this scale and expanded to larger areas. Given the high density and mixed-use nature of Hong Kong's urban areas, we begin with a local environment of 100 m. Many residential buildings in the urban areas of Hong Kong have shops in their ground floors, thus it is not unusual in Hong Kong to find all neighborhood necessities within 100 m. The median size of the aerial units for which census data are tabulated in Hong Kong is 0.05 km^2, which corresponds to a circle of 120 m radius. The difference in the size of a neighborhood considered in a given urban context underscores the usefulness of a segregation measure that is scale consistent as it facilitates comparison between two very different contexts.

3.2. Small area census data on household income in the two cities

For Hong Kong, data on household income from the Population Census and By-Census of the years 1991, 1996, 2001, and 2006 were used to calculate the various measures of segregation (Census and Statistics Department, 1992, 1997, 2002, 2006, 2007a). Income is tabulated and reported by the Hong Kong Census and Statistics Department in 11 categories in 1991 and 12 categories in 1996–2006. Data are analyzed at the smallest geographic area for which data are available; the Large Street Block Group (LSBG). Street block groups are clusters of street blocks defined by the Census and Statistics Department. Fig. 3 shows the boundaries of some of the roughly 1500 LSBGs in Hong Kong, focusing on the central urban area of Kowloon. It also displays an example of the concentric rings of 100, 200, 500, 1000, 2000, and 4000 m that are used to define local environments for the estimation of spatial segregation indices.

For San Francisco, data from the decennial census of 2000 is used to calculate indices (US Census Bureau, 2000). Household incomes are tabulated and reported in 16 categories. The smallest geographic area for which income data are available in the United States is the block group. Given the high density of Hong Kong and the fact that methods used in this paper have been used only in the US context until now, it is important to understand how data reporting differs between the two. Thus, Fig. 3B shows the boundaries of census block groups in the San Francisco metropolitan area along with concentric rings of varying radii. The San Francisco MSA had over 4 million residents in the year 2000 whereas Hong Kong had almost seven. But more importantly, Hong Kong was about 14 times as densely populated as San Francisco metropolitan area in that year.[6] Both cities have strong regulation of land use. In spite of the laissez-faire reputation of Hong Kong, the government is the sole landowner and since the 1970s it has used its power to concentrate new housing developments of high densities in a relatively dispersed manner throughout the New Territories (Forrest et al., 2004).

Table 1 reports descriptive statistics of LSBGs in Hong Kong and Census tracts and block groups in the San Francisco metropolitan area. The LSBG in Hong Kong is roughly comparable to the block group in San Francisco in terms of the median number of households (670 as compared to 470), although LSBGs have a much greater variation in the number of people covered. Of course the LSBG is much smaller geographically than a block group in San Francsico – the median LSBG is roughly one tenth that of the median block group. Yet, the variation in size of LSBG is dramatically smaller. The sharp contrast in the variation between geographic and population size in the two

[3] Although there were changes in the legal status of Hong Kong residents after 1997, immigration policy per se did not change and there was no large influx of people from mainland China. The share of the population born in mainland China dropped between 1991 and 2006, from 34 to 32%.

[4] Calculated using Donaldson–Weymark relative S-Gini and the 1% sample, excluding households for which data were not available. The Gini coefficient reported by the Census and Statistics Department (2007b) for 1996 was 0.51 and for 2006 was 0.53. Those reported by Lui (2011) for the working population were 0.39 in 1986 and to 0.43 in 2006.

[5] An estate is a group of homogenous apartment buildings developed together.

[6] San Francisco metropolitan area had about 130 households per square kilometer whereas Hong Kong had about 1800.

Fig. 3. A. Boundaries of Large Street Block Groups in 2001, and Circles of Radius 100, 200, 500, 1000, 2000 and 4000 m, Kowloon. Source: Authors with Census and Statistics Department (2002). B. Boundaries of Block Groups in 2000, and Circles of Radius 100, 200, 500, 1000, 2000 and 4000 m, San Francisco. Source: Authors with US Census Bureau (2000).

areal units results from how they are drawn. The United States Census Bureau draws boundaries in order to have relatively consistent populations across units whereas the LSBGs in Hong Kong are designated in order to have a similar geographic size, though blocks in Hong Kong are combined where their populations are lower than 1000.

Table 1
Census tabulation areas in Hong Kong and San Francisco, 2001/2000.

Geographic unit	Households (thousands)			Area (km^2)		
	Mean	Median	SD	Mean	Median	SD
Large Street Block Group (Hong Kong)	1.29	0.67	1.55	0.70	0.05	3.58
Census Tract (San Francisco)	1.77	1.67	0.78	13.20	1.66	69.24
Block Group (San Francisco)	0.56	0.47	0.34	4.20	0.44	27.91

Source: Census and Statistics Department (2002) and US Census Bureau (2000).

The difference between the two methods for drawing census area boundaries draws attention to the fact that although the grid cell method allows for the creation of neighborhoods of different sizes, it does not eliminate the impact of the composition of census units on the base data. On the one hand, emphasizing a similar geographic size for census units, as in Hong Kong's LSBG system, is preferable for analysis of spatial patterns as their geography is more consistent. On the other hand, however, it likely puts a downward bias on measures of segregation as dense neighborhoods can have very large population counts in one block.

4. Analysis of socioeconomic segregation

In order to measure levels of socioeconomic segregation in Hong Kong, a series of spatial segregation indices are calculated; a simple multi-group entropy index, an ordinal entropy index, and a rank-order index. Non-spatial values of these indices are also reported for comparison purposes. As mentioned earlier, converting small area units into grid cells and reconfiguring local environments alters the aerial units for which segregation indices are calculated. This leads to lower segregation values than the non-spatial indices when the new local environments include grid cells generated from neighboring sub-units. This is especially true in the case of Hong Kong as the smallest local environment for which we calculate a segregation index, that of a 100 m radius, is an area of 0.03 km^2, which is smaller than the median (and mean) size of LSBG. Thus, more than half of the local environments contain data from more than one LSBG.

Table 2 reports values for the six indices in the four time periods for which it was measured in Hong Kong and for the year 2000 in San Francisco. The non-spatial calculations are for the original census tabulation units, and the spatial versions of the index are reported for a local environment of a 100 m radius circle. Values for other sizes of local environment are reported in Fig. 4 below. As expected, the ordinal index of segregation is consistently larger than the multi-group index, roughly 50% in most years. This reflects the fact that the multi-group treats all income categories as equal, which does not reflect the ordinal nature of income groups.

In comparable years, the indices of segregation for Hong Kong are almost identical to the average value reported for 100 US metropolitan areas; for example, the non-spatial rank-order index of segregation was 0.16 in 2000 (Reardon and Bischoff, 2011). If we consider United States

Table 2
Non-spatial and spatial indices of Segregation in Hong Kong and San Francisco, 2001/2000.

	Non-spatial indices			Spatial indices (100 m radii)		
Year	Multi-group	Ordinal	Rank-order	Multi-group	Ordinal	Rank-order
Hong Kong						
1991	0.100	0.159	0.142	0.087	0.143	0.126
1996	0.096	0.145	0.141	0.081	0.129	0.126
2001	0.101	0.151	0.158	0.085	0.132	0.138
2006	0.095	0.138	0.142	0.080	0.121	0.125
San Francisco MSA						
2000	0.099	0.131	0.133	0.091	0.126	0.129

Source: Authors' calculation with Census and Statistics Department (1992, 1997, 2002, 2007a) and US Census Bureau (2000).

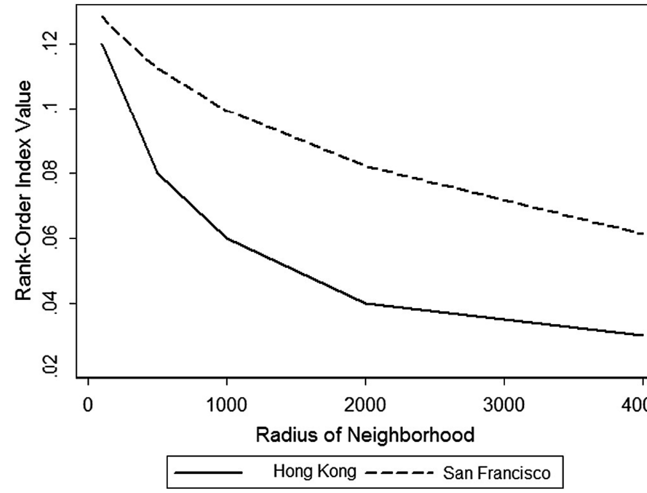

Fig. 4. Rank-order Spatial Entropy Indices in Hong Kong and San Francisco. Source: Authors with Census and Statistics Department (2002) and US Census Bureau (2000).

cities to be highly segregated, in comparison to European cities for example (Musterd, 2005), segregation levels in Hong Kong should also be considered high. However, most of these 100 cities are smaller than Hong Kong and have lower levels of inequality; the average Gini of the 100 US cities was 0.40 in 2000 as compared to 0.42 in Hong Kong.

The comparison to the San Francisco metropolitan area reveals a more complex difference. The rank-order index calculated at 200 m was 0.123 in Hong Kong and 0.121 in San Francisco, whereas when calculated at 500 m it was 0.089 in Hong Kong and 0.110 in San Francisco. Examining changes in segregation levels in increasingly larger areas yields more information about the spatial nature of segregation in a city. Fig. 4 presents values of the three indices estimated for different sizes of neighborhood in Hong Kong and San Francisco. The segregation index drops at an exponential rate in Hong Kong as the size of the area for which it is tabulated increases, whereas in San Francisco it declines gradually and linearly.

The rate at which segregation levels fall indicates whether overall levels of segregation stem from micro or macro trends. One way to measure this dynamic is a macro/micro ratio (Reardon et al., 2006), which is obtained by dividing segregation levels for large local environments, in this case those of 4000 m radii, to those of small local environments, in this case 500 m. A low macro/micro ratio indicates that the city tends toward small, economically homogenous neighborhoods adjacent to neighborhoods of a different make-up, rather than large areas of economically similar households. The macro/micro ratio is much lower in Hong Kong than in the United States. In 2001, the macro/micro ratio was 0.32 in Hong Kong whereas for San Francisco in 2000 it was 0.56, illustrating that segregation persists at a larger scale.

The difference in the relationship between segregation levels and geographic scale between the two cities is not surprising given the contrasting urban environments. The high-rise built environment and high population density of Hong Kong means that the number of households grows very rapidly and neighborhood size is increased. Further, the scattered concentrations of high density housing development contribute to a smaller scale of homogenous neighborhoods in much of the city. On the other hand, it is likely that the political fragmentation and the prevalence of single-family housing lead to a larger size of homogenous neighborhoods in much of the San Francisco metropolitan area. The creation of relatively homogenous suburban cities is well-documented feature of US urban development (Mieszkowski and Mills, 1993).

The difference between the two cities' spatial scale of segregation illustrates the challenge of measuring spatial segregation with simple Euclidean distance. Hong Kong's rapid drop in segregation at larger scales is surely due to much more people being included in the calculation, but this does not necessarily mean they are actually more likely to overlap in physical space. The question of the probability of contact due to proximity is not addressed in these calculations. In some cases, for example, residential units separated by major roads, there are physical barriers beyond distance. However, other elements of the urban environment matter as well. In cities with a car-based transit system neighbors are much less likely to cross paths than in a city, like Hong Kong, in which public transit is predominant. These issues are important for a more precise measurement of the phenomenon but would depend in part on more geographically detailed (building level) socioeconomic data.

Income inequality increased consistently from 1991 to 2006 in Hong Kong, but levels of segregation did not change dramatically. Some, but not all, of this discrepancy is explained by the categorization of income data. Gini coefficients reported earlier were calculated using more detailed income data than is available in georeferenced format. Due to privacy concerns, the Census and Statistics Department reduce the top coded category to 60,000 Hong Kong Dollars[7] (HKD) per month from the 100,000 HKD reported in geographically aggregated data. The Gini coefficient for Hong Kong calculated using the georeferenced income data employed in the segregation calculations was 0.39 in 1991 and 0.42 in 1986. Therefore, some of the increase in inequality came from an increase in earnings at the highest end of the income distribution but inequality increased considerably even among the bulk of the population. The reason this has not manifested itself spatially could be due to short term trends of urban redevelopment in inner urban areas, which temporarily places high-income households in new residential buildings near older stock inhabited by low-income households. Another explanation is the siting of new public rental estates near public ownership and private housing estates that generally have residents of much higher incomes.

The pattern of segregation across the income distribution in Hong Kong contrasts sharply with that found in the United States. Reardon et al. (2006) present similar graphs for several US cities, all of which have a flat U-shape with less variation. Lower-income households generally experience a similar level of segregation as high-income households in the United States, and segregation levels are quite similar for the 30th to the 70th percentile. In Hong Kong, on the other hand, segregation levels are lowest for the 20th percentile and increase rapidly as incomes grow. Households in the 90th income percentile are more than twice as segregated as those in the 10th percentile.

A direct comparison between segregation across the income distribution in Hong Kong and the San Francisco metropolitan area is presented at two spatial scales in Fig. 5A and B. For a 200 m radius neighborhood, the segregation profile of San Francisco is less U-shaped than other US cities presented by Reardon et al. (2006), but nothing like the almost linear form of Hong Kong. Clearly, low-income households are less segregated in Hong Kong than they are in San Francisco, whereas high-income households in Hong Kong are much more isolated.

The difference between the two cities has two probable causes. The first is the fact that almost a third of Hong Kong's low-income population lives in public rental housing, which is relatively mixed-income and often located near middle-income and high-income neighborhoods. A simple test of this hypothesis is possible using population census data from 2006 that are cross-tabulated data by housing type and income[8] at the LSBG level. First, we estimate the share of households that are middle- and high-income within different neighborhood sized for each LSBG, and then compare the average share of middle-income and high-income households within 200 m of low-income households in public

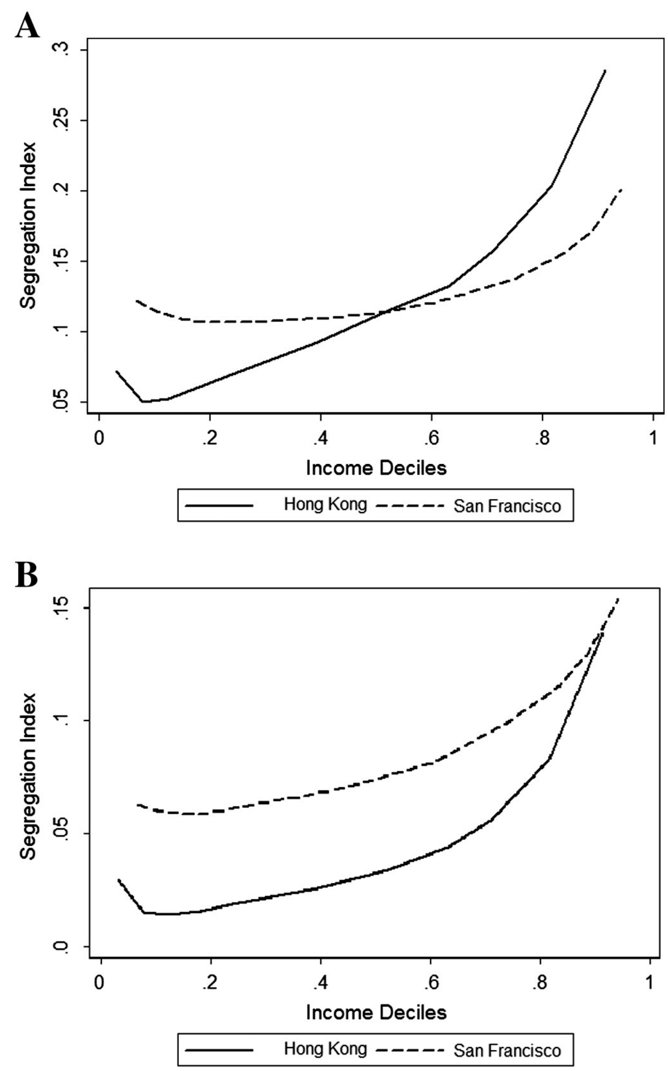

Fig. 5. A. Income Segregation in Hong Kong and San Francisco at 200 m. Source: Authors with Census and Statistics Department (2002) and US Census Bureau (2000). B. Income Segregation in Hong Kong and San Francisco at 2000 m. Source: Authors with Census and Statistics Department (2002) and US Census Bureau (2000).

housing and low-income households not living in public housing. For the average low-income public housing resident, 48% of neighbors are middle income and 21% are high income, whereas for residents of private housing these numbers are 43 and 28%.[9] Thus, public housing places low-income households closer to middle-income households but farther from high-income households, which supports its suggested impact on the overall pattern of segregation across the income distribution.

A second possible cause of the different patterns of segregation across the income distribution is differences between patterns of urban growth. In the United States, cities have tended to expand through the creation of new suburban jurisdictions for middle- and upper-income households, which in many cases means that central cities have a concentration of lower-income households (Schmidheiny, 2006). In Hong Kong, urban expansion is often through the joint development of public and private housing, but central city redevelopment has been continuous throughout the city's history and high-income households occupy central parts of the city. This is not a new argument (Forrest et al., 2004), but the hypothesis has not yet been tested empirically.

The pattern of segregation for a larger size of neighborhood – a circle of 2000 m radius – is presented for both cities in Fig. 5B. The patterns contrast with the smaller scale in both cases. San Francisco becomes

[7] The exchange rate between HKD and USD has been pegged at around 7.8 since the 1980s.

[8] For privacy considerations, the Census and Statistics Department of Hong Kong reduces the number of income categories from 11 to four when releasing cross-tabulated data. Thus, for 2006, the categories are less than 10,000 HKD/month, from 10,000 to 20,000, from 20,000 to 30,000, and above 30,000. These groups correspond roughly to the 25th, 50th, and 75th percentiles of the household income distribution.

[9] The relative numbers change very little for different sizes of neighborhood.

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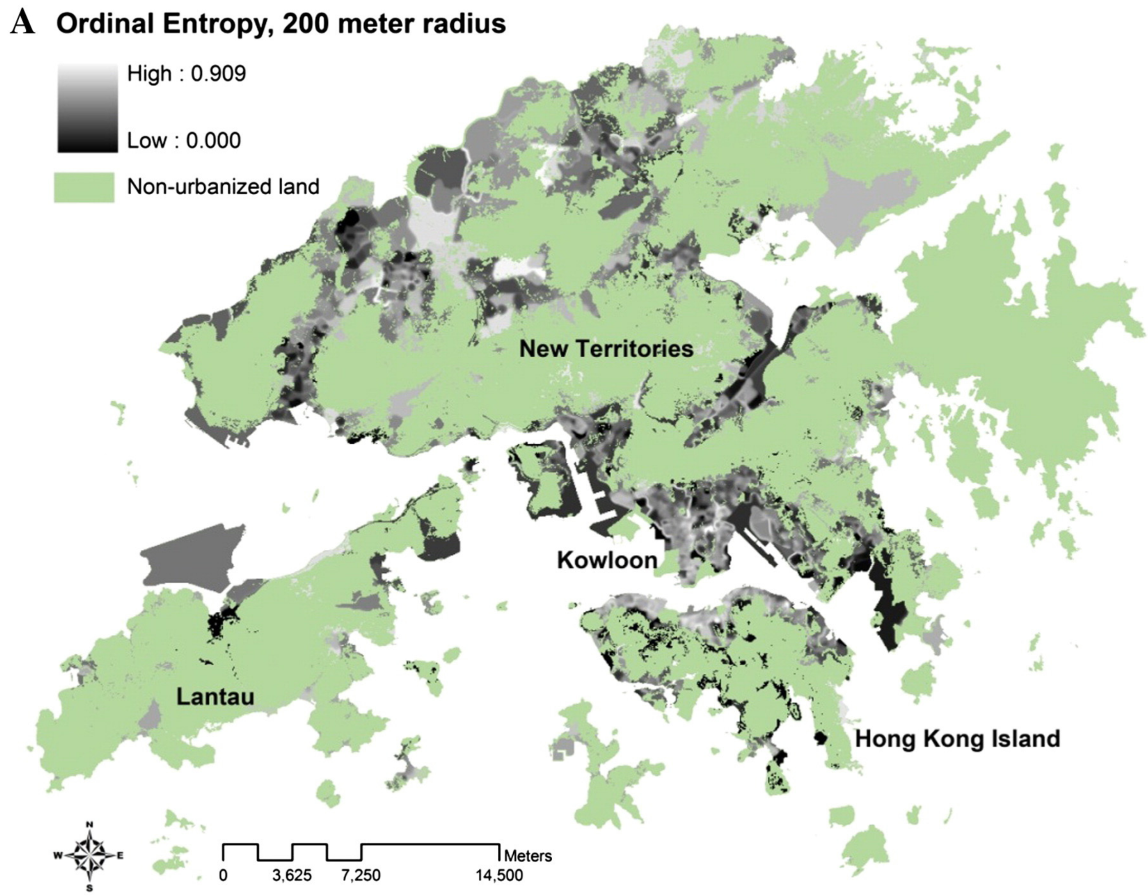

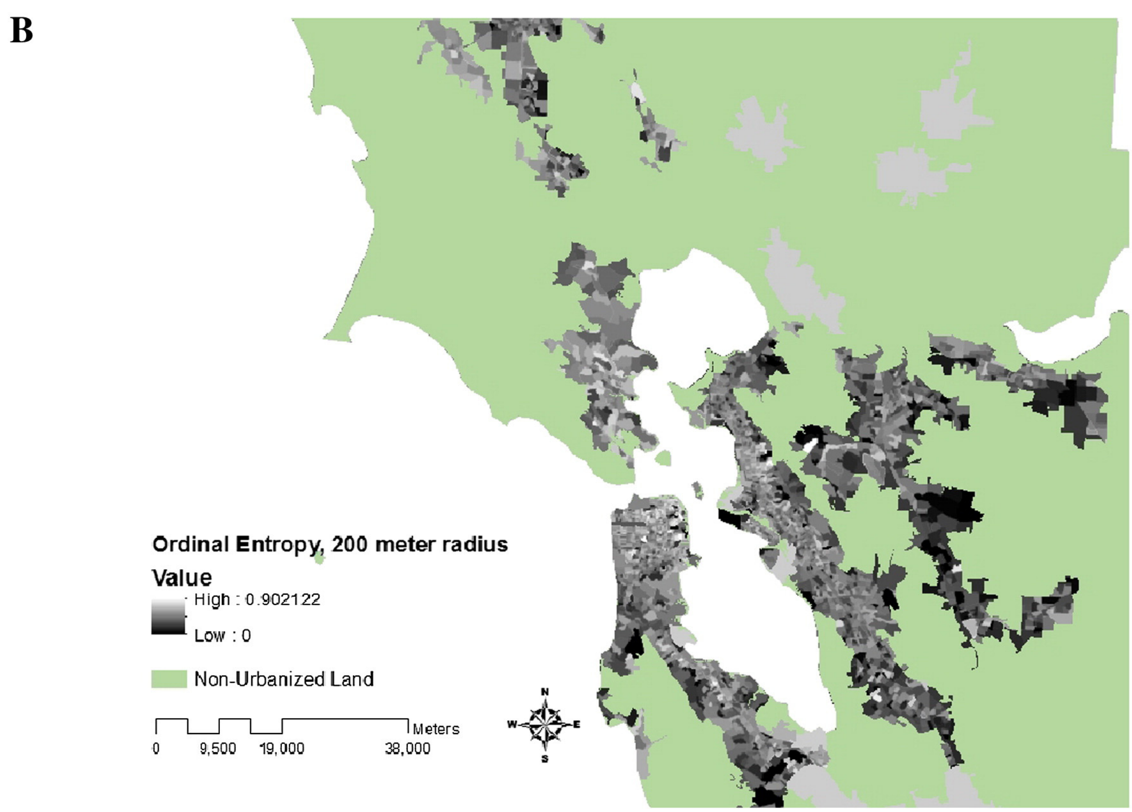

Fig. 6. A. Ordinal entropy values at 200 m radius in urban Hong Kong, 2006. Source: Authors with Census and Statistics Department (2007a). B. Ordinal entropy values at 200 m radius in San Francisco, 2000. Source: Authors with US Census Bureau (2000).

more linear and Hong Kong flatter. This reflects the larger scale of spatial separation for rich households in San Francisco, who tend to live in low-density neighborhoods. In Hong Kong, it shows that the integration of low-income households is more prevalent at a small scale, perhaps within the public housing itself.

Fig. 6A and B presents the ordinal entropy for LSBG calculated for at local environment of a 200-m radius in the year 2006. These entropy values are not measures of segregation per se; rather, they are measures of heterogeneity of neighborhood residents. Lighter areas are more economically diverse, while darker areas are more homogenous. Given the relationship between income and segregation in Hong Kong described above, it is not surprising to see that neighborhoods with a higher median income tend to be more homogenous (i.e., darker). Similarly, in San Francisco, the high-income suburban areas are also more homogenous, though the difference in neighborhood diversity is less stark than in Hong Kong.

5. Conclusion

This paper presents an analysis of segregation levels across spatial scales and the income distribution in the high-density and highly unequal city of Hong Kong, with a comparison to the San Francisco metropolitan area. At small scales, segregation in Hong Kong is high, similar to that of US cities on average and San Francisco in particular. Although a rough measure yields similar levels of segregation in Hong Kong and San Francisco at a small scale, the disaggregated analysis finds sharp distinctions between the scale and distributional nature of segregation in the two places. The comparison suggests that the built environment plays a crucial role in the level and scale of segregation. In contrast to the metropolitan area of San Francisco, the high-rise residential buildings scattered around a mountainous landscape in Hong Kong lead to a small size of homogenous neighborhoods, and segregation levels fall rapidly as the geographic scale of measurement is increased.

Yet, the second major difference between the two cities is less easily explained. The shape of the segregation profile across the income distribution in Hong Kong contrasts sharply with that of US cities; segregation in Hong Kong increases almost exponentially with household income. There are several possible explanations for this feature of segregation in Hong Kong. For example, high population density and high land prices have created an urban landscape in which proximity to the city center and transport matters more than in other contexts (Cervero and Murakami, 2009). Thus, there is a greater differentiation between adjacent neighborhoods (Monkkonen et al., 2012). The mountainous and island geography of Hong Kong also contributes to the great differentiation among neighborhoods and actually increases their physical distance from one another.

One explanation for socioeconomic segregation increasing with income is that roughly one half of Hong Kong's population, mostly lower-income households, live in public housing (Census and Statistics Department, 2007a). Given the long history of public housing development, estates can be found across the city and adjacent to neighborhoods otherwise inhabited by middle- and high-income households. This surely contributes to the low levels of segregation found among low-income groups. Clearly, more targeted research on the role of public housing in patterns of spatial segregation in Hong Kong is needed. Additionally, the challenge of redeveloping multi-owner properties mean that redevelopment of older urban areas by private parties is often piecemeal. This has led to a heterogeneous housing stock in many central parts of the city; where low-income households continue to inhabit older buildings adjacent to new luxury high-rises (Ng, 2002).

Whatever the cause, the segregation profile of Hong Kong contributes to an important twist in the existing literature, and leads to two important areas of further research. Beyond explaining why the pattern is different, we must ask whether it is a unique case or typical of cities outside of the United States. Additionally, the implications of this pattern of segregation should be studied. Other than the sorting literature that began with Tiebout (1956), the phenomenon of socioeconomic segregation has generally been approached with a concern for the concentration or marginalization of poverty (Massey and Kanaiaupuni, 1993; Jargowsky, 2002). The broader social impacts of isolation of high-income groups, on the other hand, have gotten less attention.

The social implications of the different segregation profiles found in Hong Kong and US cities merit further attention and normative debate. Is the relative integration of low-income households worth the isolation of the rich? Some evidence suggests that the Hong Kong profile is preferable. Recent work on social mix at the neighborhood level in Sweden found that living near middle-income households provides benefits to lower-income households, whereas living near high-income households does not (Galster et al., 2008). Whether this is also the case in Hong Kong remains to be seen.

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Appendix A. Three non-spatial segregation indices

This appendix restates the calculation of three non-spatial segregation indices: the multi-group entropy index (Reardon and Firebaugh, 2002), the ordinal entropy index (Reardon, 2009), and the rank-order entropy index (Reardon et al., 2006).

1. The multi-group entropy index (H) is essentially a weighted average of the entropy of sub-units of the city compared to the citywide entropy. It is estimated as follows:

$$\mathrm{H} = 1 - \frac{1}{TE}\sum_{j=1}^{J} t_j E_j \tag{1}$$

where

T	the total number of residents;
tj	number of residents in sub-unit j (j indexes sub-units);
E	the overall entropy of the city; and
E_j	the entropy in block j.

The entropy for the whole city is calculated as follows:

$$\mathrm{E} = \sum_{m=1}^{M} \pi_m \log_M \frac{1}{\pi_m} \tag{2}$$

where

π_m	proportion of the population in income group m; and
M	number of income groups.

The entropy for each sub-unit is calculated as follows:

$$\mathrm{E}_j = \sum_{m=1}^{M} \pi_{jm} \log_M \frac{1}{\pi_{jm}} \tag{3}$$

Where

π_{jm} proportion in group m in block j.

2. The ordinal entropy index (Λ) is similar to the multi-group entropy index, except that rather than using simple income categories,

groups are defined as the cumulative percentage of households below a certain income level. Thus, the index is calculated:

$$\Lambda = \sum_{j=1}^{J} \frac{t_j}{T} \cdot \frac{v - v_j}{v} \tag{4}$$

Where v is the entropy calculated using cumulative income groups (c_m), which are defined below. Note that log of base two is used so that the index has a maximum value of one.

$$v = -\frac{1}{M-1} \sum_{m=1}^{M-1} c_m \log_2 c_m + (1 - c_m) \log_2 (1 - c_m) \tag{5}$$

Cumulative income shares (c_m) are the sum of the proportion of the population in income groups (k), which are less than and equal to each income category m. The formula is as follows:

$$c_m = \sum_{k=1}^{m} \pi_k \tag{6}$$

As with the multi-group index, the entropy based on cumulative income groups is also calculated for sub-units of the city indexed by j:

$$v_j = -\frac{1}{M-1} \sum_{m=1}^{M-1} c_{jm} \log_2 c_{jm} + \left(1 - c_{jm}\right) \log_2 \left(1 - c_{jm}\right) \tag{7}$$

$$c_{jm} = \sum_{k=1}^{m} \pi_{jk} \tag{8}$$

3. The rank-order entropy index (H_R) can be thought of as an extension of the ordinal index described above. The general form is defined as follows:

$$H_R = \int_0^1 \frac{E(g)}{\int_0^1 E(g) dg} H(g) dg \tag{9}$$

Where $H(g)$ and $E(g)$ are pairwise segregation indices and entropy values calculated as the segregation and entropy for those with incomes below every point g along the income distribution and those with incomes above that point.
In practice, we estimate $\hat{H}_R$ in a two-step process. First, pairwise segregation indices $H(g)$ and entropy values $E(g)$ are computed that compare the segregation of households at each point g in the income distribution:

$$H(g) = 1 - \frac{1}{TE(g)} \sum_{j=1}^{J} t_j E_j(g) \tag{10}$$

Where T and tj are defined as in the multi-group entropy index, and $E(g)$ and $E_j(g)$ are the entropy values for cumulative income group at point g on the distribution citywide and in sub-unit j, defined as follows:

$$E(g) = g \log_2 \frac{1}{g} + (1 - g) \log_2 \frac{1}{1 - g} \tag{11}$$

$$E_j(g) = \pi_{jg} \log_2 \frac{1}{\pi_{jg}} + \left(1 - \pi_{jg}\right) \log_2 \frac{1}{1 - \pi_{jg}} \tag{12}$$

In this way, we calculate M-1 pairwise segregation indices. These indices are then used as the dependent variable in a regression that approximates the polynomial function of order w:

$$\hat{H}(g) = \hat{\eta}_0 + \hat{\eta}_1 g + \hat{\eta}_2 g^2 + \cdots + \hat{\eta}_w g^w \tag{13}$$

Finally, we calculate $\hat{H}_R$ by plugging in the parameter estimates from Eq. (13) to the following equation, the derivation of which can be found in Reardon et al. (2006).

$$\hat{H}_R = \hat{\eta}_0 + \frac{1}{2}\hat{\eta}_1 + \frac{11}{36}\hat{\eta}_2 + \frac{5}{24}\hat{\eta}_3 + \cdots + \left[\frac{2}{(w+2)^2} + 2\sum_{n=0}^{w} \frac{(-1)^{w-n}({}_wC_n)}{(w-n+2)^2}\right]\hat{\eta}_w \tag{14}$$

Appendix B. Three spatial segregation indices

This appendix summarizes the calculation of the spatial counterparts to the segregation indices presented in Appendix A. The technique is a restatement of that presented by Reardon and O'Sullivan (2004) and applications in Reardon et al. (2008) and Lee et al. (2008). The calculations mirror the non-spatial indices in Appendix A, but instead of sub-units defined by census data, sub-units are a large number of local environments surrounding points. In this case, points are grid cells. Given the large number and potentially very small size of these points, integrals are used rather than weighted averages.

1. The spatial multi-group entropy index $\left(\tilde{H}\right)$ is defined as follows:

$$\tilde{H} = 1 - \frac{1}{TE} \int_{p \in R} \tau_p \tilde{E}_p dp \tag{1}$$

Where T and E are defined as in Appendix A1;

p points used as the center of local environments (grid cells);
R the region on which the segregation index is calculated;
τ_p population density in p; and
$\tilde{E}_p$ entropy of the local environment of point p. It is defined as:

$$\tilde{E}_p = \sum_{m=1}^{M} \tilde{\pi}_{pm} \log_M \frac{1}{\tilde{\pi}_{pm}} \tag{2}$$

$\tilde{\pi}_{pm}$ denotes the proportion of group m in local environment of point p, defined as:

$$\tilde{\pi}_{pm} = \frac{\int_{q \in R} \tau_{qm} \varnothing(p,q) dq}{\int_{q \in R} \tau_q \varnothing(p,q) dq} \tag{3}$$

Where

τ_{qm} population density of group m in the point q;
τ_q population density in the point q; and
$\varnothing(p,q)$ a distance-decay function. As discussed in the article, the local environment can be defined in a number of ways. We follow Reardon and O'Sullivan (2004) and use a biweight kernel proximity function based on several radii (r), defined as:

$$\varnothing(p,q) = \begin{cases} \left[1 - \left(\frac{d(p,q)}{r}\right)^2\right]^2 & \text{if } d(p,q) < r \\ 0 & \text{if } d(p,q) \geq r \end{cases} \tag{4}$$

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Where the function $d(p,q)$ is simply the Euclidean distance between p and q.

2. The spatial ordinal entropy index $(\widetilde{\Lambda})$ is defined as follows:

$$\widetilde{\Lambda} = \int_{p \in R} \frac{t_p}{T} \cdot \frac{v - \widetilde{v}_p}{v} \quad (5)$$

Where T, t_p, and v are defined as in Appendix A2, but $\widetilde{v}_p$ is as follows:

$$\widetilde{v}_p = -\frac{1}{M-1} \sum_{m=1}^{M-1} \widetilde{c}_{pm} \log_2 \widetilde{c}_{pm} + \left(1 - \widetilde{c}_{pm}\right) \log_2 \left(1 - \widetilde{c}_{pm}\right) \quad (6)$$

Where $\widetilde{c}_{pm}$ is the cumulative income share in the local environment of p as defined below. Similar to the non-spatial ordinal entropy index, cumulative income shares are defined for each point.

$$\widetilde{c}_{pm} = \sum_{k=1}^{m} \widetilde{\pi}_{pk} \quad (7)$$

$\widetilde{\pi}_{pk}$ is defined as $\widetilde{\pi}_{pm}$ in Eq. (3) using values from neighboring points and a distance decay function.

3. Spatial rank-order entropy index is defined in a general form as follows:

$$\widetilde{H}_R = 2 \ln 2 \int_0^1 \widetilde{E}(g) \widetilde{H}(g) dg \quad (8)$$

Where $\widetilde{H}(g)$ and $\widetilde{E}_p(g)$ are defined as:

$$\widetilde{H}(g) = 1 - \frac{1}{TE(g)} \int_{p \in R} \tau_p \widetilde{E}_p(g) dp \quad (9)$$

and

$$\widetilde{E}_p(g) = \widetilde{\pi}_p(g) \log_2 \frac{1}{\widetilde{\pi}_p(g)} + \left(1 - \widetilde{\pi}_p(g)\right) \log_2 \frac{1}{\widetilde{\pi}_p(g)} \quad (10)$$

$\widetilde{\pi}_p(g)$ denotes the share with income at or below the income percentile g in the local environment of point p, and is defined as:

$$\widetilde{\pi}_p(g) = \frac{\int_{q \in R} \tau_q(g) \varnothing(p,q) dq}{\int_{q \in R} \tau_q \varnothing(p,q) dq} \quad (11)$$

Where $\tau_q(g)$ is the density of the population below income percentile g in point q.

Appendix C. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.regsciurbeco.2013.09.016.

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