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Exploring the global and local patterns of income segregation in Toronto, Canada: A multilevel multigroup modeling approach

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Abstract

Residential income segregation is a spatial manifestation of social inequality and is an important factor that influences access to resources, services, and amenities. In general, past research analyzing income segregation has applied index-based methods to describe the separation of low-income households at one spatial scale; however, existing studies have not yet considered how income segregation varies across multiple income classes, spatial scales, and local contexts. This study applies a multilevel multigroup modeling approach to explore the global and local patterns of income segregation between dissemination areas (micro-scale), census tracts (meso-scale), and neighborhoods (macro-scale) in Toronto, Canada. A global model that estimates the overall multiscale segregation of five income classes finds that the most affluent families had the highest levels of segregation and that the segregation of all income classes was strongest at the macro- and micro-scales. A local model that allows the micro-scale segregation measures to vary geographically shows that higher-income families were less segregated in the city center than in the inner suburbs, that middle-income families were highly segregated in areas serviced by public transit, and that almost all income classes had high levels of segregation in disadvantaged neighborhoods prioritized for investment by local policymakers. The methodological and substantive contributions of this study for understanding the complex patterns of income segregation are discussed.

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Segregation, income, multilevel model, local spatial analysis, complex variance

Introduction

Residential income segregation, or the uneven distribution of households across geographical units according to income, is a spatial manifestation of the demographic, economic, and political processes associated with social inequality (Massey et al., 2009; Slater, 2013). Income segregation also shapes access to housing, employment, educational opportunities, and public services and amenities, as well as exposure to social and environmental hazards (Acevedo-Garcia, 2001; Owens, 2018; Reardon, 2006). In general, studies that analyze residential income segregation have applied index-based methods, such as the index of dissimilarity, to measure the spatial separation of low-income families from non-low-income families (Ades et al., 2012; Fong and Shibuya, 2000; Jargowsky, 1996; Massey and Eggers, 1993; Reardon and Bischoff, 2011). While index-based methods have been developed to analyze multiple social or income groups (Sakoda, 1981) and to identify and visualize the local intra-urban patterns of segregation (Feitosa et al., 2007; O'Sullivan and Wong, 2007), conventional indices measure segregation at only one spatial scale (or for one set of areal units). More recently, studies have suggested that multilevel models be used to examine how segregation manifests across multiple spatial scales (Goldstein and Noden, 2003; Harris, 2017; Jones et al., 2015). However, multilevel modeling approaches have yet to be applied to analyze income segregation for multiple scales and income classes, nor have model-based approaches been developed to investigate if and how segregation varies geographically within a city or region (Jones et al., 2018).

This study applies a multilevel multigroup modeling approach to examine the global and local patterns of residential income segregation at three spatial scales in Toronto, Canada. The counts of families in five income classes were measured at the micro-scale (dissemination area (DA)), and each micro-area was hierarchically nested in one meso-area (census tract (CT)) and one macro-area (neighborhood). Global and local multilevel segregation models are compared. The global model estimates the overall segregation of each income class at the micro-, meso-, and macro-scales and assumes constant scale- and class-specific levels of segregation for the study region. The local models allow the micro-scale segregation estimates to vary geographically within meso- and macro-areas according to observed covariates, specifically urban development characteristics, public transit service, and place-based policies, as well as latent random effect terms.

This study illustrates the first application of a multilevel modeling approach for the joint analysis of global and local segregation at multiple spatial scales. The models developed in this study integrate the place-based focus of local segregation indices (Feitosa et al., 2007; O'Sullivan and Wong, 2007) within the modeling frameworks employed in contemporary multiscale segregation research (Goldstein and Noden, 2003; Jones et al., 2018; Leckie et al., 2014) while simultaneously quantifying how local segregation patterns are associated with characteristics of the urban environment. Enabled by this methodological contribution, this study provides a more comprehensive picture of income segregation than past research focused on only low-income families at one scale. In this study, global income segregation is found to be driven by the macro-scale separation of the most affluent families. At the local scale, however, income segregation is characterized by low segregation of higher-income families in the city center, high segregation of middle-income families in areas serviced by public transit, and high segregation of almost all income classes in disadvantaged communities prioritized for investment by local policymakers.

The remainder of this paper is structured as follows. First, the methods used to analyze global and local patterns of segregation are reviewed. Next, the data and study region are described, the multilevel models are detailed, and the results are presented. Finally, the contributions of this study for understanding residential income segregation are discussed, the limitations are highlighted, and directions for future research are proposed.

Measuring and modeling urban segregation

In general, studies exploring urban segregation have applied index-based methods that quantify the spatial separation of two social or income groups at one spatial scale (Ades et al., 2012; Fong and Shibuya, 2000; Massey and Eggers, 1990; Ross et al., 2004). The index of dissimilarity, for example, describes the (un)evenness of two groups for one set of areal units and, as applied to income, is interpreted as the proportion of low or non-low-income families that must relocate to a different area in order for the two groups to be desegregated or evenly distributed (Duncan and Duncan, 1955; Fong and Shibuya, 2000; Winship, 1977). A number of index-based methods have been developed to measure alternative dimensions of segregation, including exposure to different populations (isolation index), the physical space occupied by groups (concentration index), and the location of groups relative to the city center (centralization index) (Ades et al., 2012; Massey and Denton, 1988). For income, in particular, the neighborhood sorting index has been used to assess segregation for continuous data (e.g. median income) (Jargowsky, 1996; Ross et al., 2001), and the rank-order theory index has been used to measure segregation for grouped or continuous data (Reardon, 2006; Reardon and Bischoff, 2011). See Winship (1977) and Reardon and Bischoff (2011) for detailed reviews of the most common segregation indices.

The aforementioned index-based methods are global and nonspatial insofar as one overall segregation measure is calculated for a city or region (Wong, 2002; Yao et al., 2018). To quantify and visualize the intra-urban patterning of segregation, local index-based methods have been developed that measure the distances between all areal pairs in a study region (i.e. between centroids), quantify the strength of between-area interactions by applying a proximity function to the distance measurements, and use the resulting spatial weights to calculate a local segregation index for each area (Reardon and O'Sullivan, 2004; Wong, 2002). For example, Feitosa et al. (2007) use local dissimilarity, exposure, isolation, and neighborhood sorting indices to explore income segregation in Brazil at a variety of bandwidth distances. This approach has also been used to study ethnic segregation in London and Sao Paulo (Barros and Feitosa, 2018), religious segregation in Northern Ireland (Lloyd and Shuttleworth, 2012), and ethnic segregation in England and Wales (Catney, 2018). To better capture the local environments surrounding each area, Roberto (2018) incorporates proximity and connectivity information, and Petrovic et al. (2018) use bespoke neighborhoods constructed from high-resolution grid cells.

A variety of additional local segregation methods have been proposed, including the location quotient and Local Moran's I (Anselin, 1995; Brown and Chung, 2006), a decomposition approach that partitions the total segregation of a study region into smaller scales of analysis (Wong, 2003), and a kernel density estimation technique that estimates a spatially-varying segregation surface that is continuous across areal boundaries (O'Sullivan and Wong, 2007). One limitation of existing global and local segregation indices, however, is that data at only one spatial scale are accommodated (Manley et al., 2019; Yao et al., 2018). While it is common for studies to assess the impact of scale by comparing the indices that result from separate analyses using different bandwidth distances or areal aggregations (Fowler, 2018; Lloyd and Shuttleworth, 2012; Reardon et al., 2008), this does not help to understand how segregation manifests at multiple scales simultaneously (Jones et al., 2015, 2018). Additionally, because local index-based methods do not quantify the associations between segregation patterns and characteristics of the urban environment, inference regarding where and why segregation is particularly high or low relies on visual interpretation of map outputs.

Building on research examining student segregation in classrooms, schools, and school districts (Goldstein and Noden, 2003; Leckie and Goldstein, 2015), recent studies have proposed that multilevel models be used to measure the multiscale segregation of urban areas. Multilevel models provide a formal statistical framework for analyzing hierarchical data (i.e. multiple lower-level units nested in one or more higher-level units) and offer a number of advantages compared to traditional index-based methods; multilevel models can jointly analyze segregation at multiple spatial scales, for multiple groups, and across multiple time periods (Johnson et al., 2016b; Jones et al., 2015); can account for uncertainty and allow for inference regarding which scales and groups have significantly higher (or lower) levels of segregation (Harris, 2017); and can accommodate complex multiple membership and cross-classified data structures that deal with the modifiable areal unit problem (Jones et al., 2018). Multilevel models can also incorporate covariates to describe the spatial pattern of each social or income group and/or to explore how segregation varies among different subsets of the data (e.g. different levels of ethnic segregation for schools in Inner and Outer London; Leckie and Goldstein, 2015).

Recently, a number of studies have applied multilevel modeling approaches to analyze the ethnic and religious segregation of cities and regions. For example, Jones et al. (2015) and Johnston et al. (2016b) focus on 13 ethnic groups at four spatial scales and 11 ethnic groups at three spatial scales in London, United Kingdom, respectively; Johnston et al. (2016a) examine 42 ancestral groups in Sydney, Australia; Manley et al. (2015) explore 4 ethnic groups at three spatial scales in Auckland, New Zealand; Arcaya et al. (2018) analyze Black and non-Black populations at three spatial scales in over 100 metropolitan areas in the United States; and Jones et al. (2018) focus on Indian and non-Indian residents at three spatial scales in Leicester, United Kingdom. However, like global index-based methods, existing multilevel analyses assume that each population group has one level of segregation for each scale and that segregation does not geographically vary within a study region. Past research has not yet considered how multilevel models can be extended to analyze local segregation patterns.

Study region and data

The study region for this research is the City of Toronto, Canada. In 2015, Toronto was Canada's most populous city, with a total population of about 2.73 million and a total geographic size of approximately 634 km^2. The counts of economic families[1] in (after-tax) income deciles at the DA scale were retrieved from the 2016 Statistics Canada Census and aggregated to income quintiles by summing the counts of families in adjacent deciles (e.g. the number of families in the lowest-income quintile was equal to the sum of the number of families in the first- and second-income deciles). As one of the smallest areal units in the Statistics Canada Census, DAs usually have populations between 400 and 700 and had an average size of 0.17 km^2 in this study region. Income quintile data were analyzed to simplify interpretation of income groups (i.e. low-, lower-middle-, middle-, upper-middle-, and high-income groups) while also providing a more comprehensive representation of the income distribution within small-areas than past research focused on only low-income families.

Descriptive statistics for the income quintile data are shown in Table 1, and the spatial pattern of each income quintile is mapped in Figure 1. On average, the lowest- and highest-income quintiles were overrepresented in Toronto relative to the national distribution, at about 25% and 24% of all families, and the second, third, and fourth quintiles were slightly underrepresented at about 18%, 17%, and 17% of all families, respectively. Geographically, areas with the highest proportions of the most affluent families were clustered in central areas of the city, whereas areas with the highest proportions of the poorest families tended to be scattered throughout Toronto. The standard deviations in Table 1 and the spatial patterns in Figure 1 suggest that the highest- and lowest-income families were relatively more segregated than the middle-income classes; about 12% of DAs had a majority of

Table 1. Descriptive statistics for the proportion of economic families at the DA scale.

Quintile	Income ($)[a]	Mean (%)	SD (%)[b]
First	Less than 27,600	23.57	13.35
Second	27,601 to 40,800	17.99	7.50
Third	40,801 to 53,600	16.52	5.71
Fourth	53,601 to 71,800	17.14	6.08
Fifth	Greater than 71,801	24.79	18.47

[a]Income ranges were retrieved from the 2016 Statistics Canada Census and are presented in 2018 constant dollars (Statistics Canada, 2020).
[b]Standard deviations for the proportion of families in each income quintile across the 3702 DAs in Toronto.

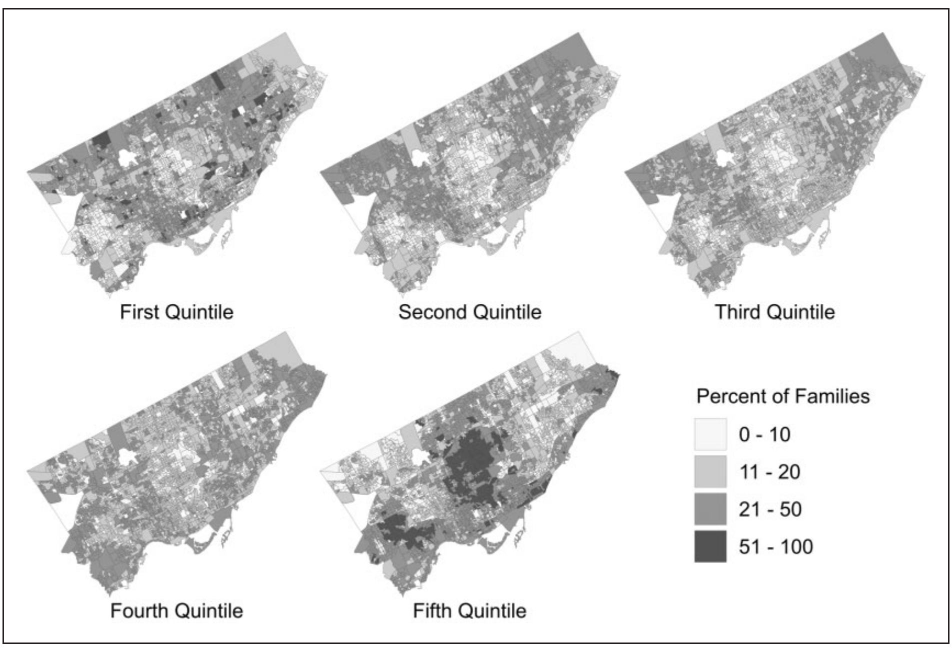

Figure 1. The spatial distribution of families in income quintiles at the DA scale.

families in the fifth quintile, 5% of DAs had a majority of families in the first quintile, and no DAs had a majority of families in the second, third, or fourth quintiles.

Micro-, meso-, and macro-scales

Income segregation was analyzed at three geographical scales: the DA or micro-scale, the CT or meso-scale, and the neighborhood or macro-scale. This operationalization recognizes that there is no single scale at which segregation manifests (Fowler, 2018; Reardon et al., 2008) and aligns with past research exploring ethnic segregation at micro-, meso-, and macro-scales (Jones et al., 2015; Manley et al., 2015). In Toronto, DAs, CTs, and neighborhoods were hierarchically structured such that each DA was completely nested in one CT and one neighborhood. CTs are a small and temporally-stable areal unit that usually have population counts between 2000 and 8000. In Toronto, CTs had an average size of 1.10 km^2. Neighborhoods were created by the City of Toronto based on the boundaries used by urban planning and public health agencies and had residential populations between 7000 and 10,000 (City of Toronto, 2020). In total, there were 3702 DAs, 569 CTs, and 140 neighborhoods; on average, 6.4 DAs were located in each CT (range of 1–14) and 26 DAs were located in each neighborhood (range of 8–67).

Describing the spatial patterns of income and income segregation

Three binary variables were selected to describe the macro-scale patterns of both income and income segregation: the city center, subway accessibility, and neighborhood improvement areas (NIAs). Location in the city center was defined using the boundaries of pre-amalgamation City of Toronto[2] to differentiate between the 44 central neighborhoods characterized by high density and mixed land uses and the 96 inner suburban neighborhoods characterized by low density and separated land uses. Subway accessibility was operationalized by assessing whether or not neighborhood boundaries intersected with 800 m buffer zones created around all subway stops. The 800 m threshold is often used to assess subway transit accessibility in urban planning practice and research (El-Geneidy et al., 2014; Ontario Ministry of Transportation, 2012). Since the subway is associated with changes to the built form and population distribution, for instance, via gentrification (Grube-Cavers and Patterson, 2015), DAs within these neighborhoods may exhibit different mixes of income groups depending on how close they are to subway stations. A total of 63 neighborhoods were considered to be accessible by the subway. NIA status was determined by the City of Toronto as part of a broader set of policies looking to support and invest in disadvantaged communities (City of Toronto, 2020). Thirty-one neighborhoods were classified as NIAs based on a variety of economic, social development, political, health, and built environment characteristics. Because NIAs are defined at the neighborhood scale, it is possible that the DAs located within any NIA include those with a majority of high-income families, a majority of low-income families, or a mix of income groups. Maps of these three macro-scale contexts are shown in the Supplementary Materials (Figure S1).

Multilevel multigroup modeling of income segregation

Let Y_{ijkq} denote the count of families in income quintile q (= 1, ..., 5) that were living in DA i (= 1, ..., 3636),[3] CT j (= 1, ..., 569), and neighborhood k (= 1, ..., 140). Following past studies using multilevel models to analyze segregation (Arcaya et al., 2018; Jones et al., 2018; Leckie et al., 2012), the counts of families in each income quintile were modeled using a Binomial likelihood with total populations n_{ijk} and proportions π_{ijkq}: $Y_{ijkq} \sim \text{Binomial}(n_{ijk}, \pi_{ijkq})$. The total populations were fixed to the number of families in each DA, and the proportions of families in each area (π_{ijkq}) were treated as unknown and modeled using the multilevel multigroup models described below.

Model 1 is a global segregation model that estimates the proportion of economic families in each income quintile (on the logit scale) as the sum of an overall intercept (α_q) and three sets of random effect terms at the macro- (λ_{kq}), meso- (u_{jkq}), and micro-scales (ϵ_{ijkq}). Each set of random effect terms was assigned a normal prior distribution with means of zero and an unknown common variance: $\sigma^2_{\lambda_q}$ for macro-areas, $\sigma^2_{u_q}$ for meso-areas, and $\sigma^2_{\epsilon_q}$ for micro-areas. These variance terms are directly estimated in the model. For interpretation, $\sigma^2_{\lambda_q}$ quantifies the macro-scale segregation for the study region, $\sigma^2_{u_q}$ quantifies the average meso-scale segregation within macro-areas, and $\sigma^2_{\epsilon_q}$ quantifies the average micro-scale segregation of families within both macro- and meso-areas (Goldstein and Noden, 2003; Jones et al., 2015). For example, a posterior estimate of $\sigma^2_{\lambda_1}$ that includes zero indicates that families in the lowest-income quintile were largely desegregated (or evenly distributed) between neighborhoods, whereas an estimate of $\sigma^2_{\epsilon_1}$ that is greater than zero indicates that the lowest-income families were segregated (or unevenly distributed) between micro-areas after adjusting for segregation at both meso- and macro-scales.

$$\text{logit}(\pi_{ijkq}) = \alpha_q + \lambda_{kq} + u_{jkq} + \epsilon_{ijkq} \tag{1}$$

$$\lambda_{kq} \sim \text{Normal}(0, \sigma^2_{\lambda_q}), u_{jkq} \sim \text{Normal}(0, \sigma^2_{u_q}), \epsilon_{ijkq} \sim \text{Normal}(0, \sigma^2_{\epsilon_q})$$

Model 2 is a local segregation model that relaxes the assumption of one scale-specific segregation measure for each income quintile and, instead, allows the micro-scale segregation measures to vary geographically across the study region. Model 2 estimates the micro-scale variance for each income quintile ($\log(\sigma^2_{\epsilon_{ijkq}})$) as the sum of an overall intercept (κ_q), a set of macro-scale random effect terms ($\lambda^{[2]}_{kq}$), and a set of meso-scale random effect terms ($u^{[2]}_{jkq}$) (Leckie et al., 2014; Lee and Nelder, 2006).[4] The choice to model heterogeneous variance terms at only the micro-scale was informed by the consistently high and low levels of segregation observed at the micro- and meso-scales in Model 1, respectively (see the Results section). In Model 2, the intercept of the micro-scale variance ($\exp(\kappa_q)$) captures the average micro-scale segregation in the study region (similar to $\sigma^2_{\epsilon_q}$ in Model 1), and the random effect terms allow the micro-scale segregation measures to depart from the study region average within each meso- and macro-area. For example, positive (negative) estimates of $\lambda^{[2]}_{k1}$ or $u^{[2]}_{jk1}$ that are unambiguously greater (less) than zero imply that the lowest-income quintile is relatively more (less) segregated in macro-area *k* and meso-area *j* than the study region average. Both $\lambda^{[2]}_{kq}$ and $u^{[2]}_{jkq}$ were assigned normal prior distributions with means of zero and a common variance for each income quintile and, as such, the degree to which the local segregation measures vary is treated as unknown and estimated in the model.

$$\text{logit}(\pi_{ijkq}) = \alpha_q + \lambda^{[1]}_{kq} + u^{[1]}_{jkq} + \epsilon_{ijkq} \tag{2}$$

$$\lambda^{[1]}_{kq} \sim \text{Normal}(0, \sigma^2_{\lambda_{q[1]}}), \quad u^{[1]}_{jkq} \sim \text{Normal}(0, \sigma^2_{u_{q[1]}}), \quad \epsilon_{ijkq} \sim \text{Normal}(0, \sigma^2_{\epsilon_{ijkq}})$$

$$\log(\sigma^2_{\epsilon_{ijkq}}) = \kappa_q + \lambda^{[2]}_{kq} + u^{[2]}_{jkq}$$

$$\lambda_{\mathrm{kq}}^{[2]} \sim \mathrm{Normal}(0, \sigma^2_{\lambda_{\mathrm{q}[2]}}), \quad \mathrm{u}_{\mathrm{jkq}}^{[2]} \sim \mathrm{Normal}(0, \sigma^2_{\mathrm{u}_{\mathrm{q}[2]}})$$

Model 3 adds three regression coefficients to explore how the spatial patterns of income (β_{nq} for $n = 1, 2, 3$) and the spatial patterns of income segregation (γ_{nq}) are influenced by the city center, subway accessibility, and NIA status. Considering location in the city center, for example, a positive (negative) estimate of β_{11} would suggest that the proportion of the lowest-income families is higher (smaller) in the city center than in the inner suburbs, and a positive (negative) estimate of γ_{11} would suggest that low-income families have higher (lower) levels of segregation in the city center than in the inner suburbs.

$$\mathrm{logit}(\pi_{\mathrm{ijkq}}) = \alpha_{\mathrm{q}} + \beta_{\mathrm{nq}} x_{\mathrm{nk}} + \lambda_{\mathrm{kq}}^{[1]} + \mathrm{u}_{\mathrm{jkq}}^{[1]} + \epsilon_{\mathrm{ijkq}} \tag{3}$$

$$\lambda_{\mathrm{kq}}^{[1]} \sim \mathrm{Normal}(0, \sigma^2_{\lambda_{\mathrm{q}[1]}}), \quad \mathrm{u}_{\mathrm{jkq}}^{[1]} \sim \mathrm{Normal}(0, \sigma^2_{\mathrm{u}_{\mathrm{q}[1]}}), \quad \epsilon_{\mathrm{ijkq}} \sim \mathrm{Normal}(0, \sigma^2_{\epsilon_{\mathrm{ijkq}}})$$

$$\log(\sigma^2_{\epsilon_{\mathrm{ijkq}}}) = \kappa_{\mathrm{q}} + \gamma_{\mathrm{nq}} x_{\mathrm{nk}} + \lambda_{\mathrm{kq}}^{[2]} + \mathrm{u}_{\mathrm{jkq}}^{[2]}$$

$$\lambda_{\mathrm{kq}}^{[2]} \sim \mathrm{Normal}(0, \sigma^2_{\lambda_{\mathrm{q}[2]}}), \quad \mathrm{u}_{\mathrm{jkq}}^{[2]} \sim \mathrm{Normal}(0, \sigma^2_{\mathrm{u}_{\mathrm{q}[2]}})$$

Model estimation and comparison

The global and local segregation models were fit using the Markov chain Monte Carlo (MCMC) algorithm in WinBUGS v1.4.3. The prior distributions for the intercepts, the regression coefficients, and the variance parameters are detailed in the Supplementary Materials. For all models, two MCMC chains were run for 20,000 iterations of burn-in and an additional 100,000 iterations were used for posterior inference, with every fifth iteration retained to reduce autocorrelation of the MCMC chains. Convergence of model parameters was monitored using visual inspection of the MCMC history plots and the Brooks–Gelman–Rubin diagnostic (Brooks and Gelman, 1998).

The Deviance Information Criterion (DIC) was used to compare Models 1, 2, and 3. The DIC assesses model fit via the sum of the posterior mean deviance ($\bar{\mathrm{D}}$), which accounts for goodness of fit between the observed data and the modeled data, and the effective number of parameters (pD), which accounts for model complexity (Spiegelhalter et al., 2002). Model evaluation using DIC is based on the relative differences between models, where models with smaller DIC values are considered to have better model fit (Lunn et al., 2012).

Results

Table 2 compares the three segregation models using the DIC. The DIC decreased between Model 1 and Model 2, suggesting that there were substantial local patterns of income segregation not captured via the global model. Model 3, which added three macro-scale covariates to describe the spatial patterns of both income and income segregation, had the smallest DIC and was identified as the best-fitting model. Note that, because the decrease in DIC between Models 1 and 2 was greater than the decrease in DIC between Models 2 and 3, accounting for the local patterning of segregation was found to be relatively more

Table 2. DIC results for the global and local segregation models.

Model	Description	$\bar{D}$	pD	DIC
1	Global segregation	132,370	16,912	149,282
2	Local segregation	132,031	16,690	148,721
3	Local segregation with covariates	132,032	16,682	148,714

DIC: Deviance Information Criterion.

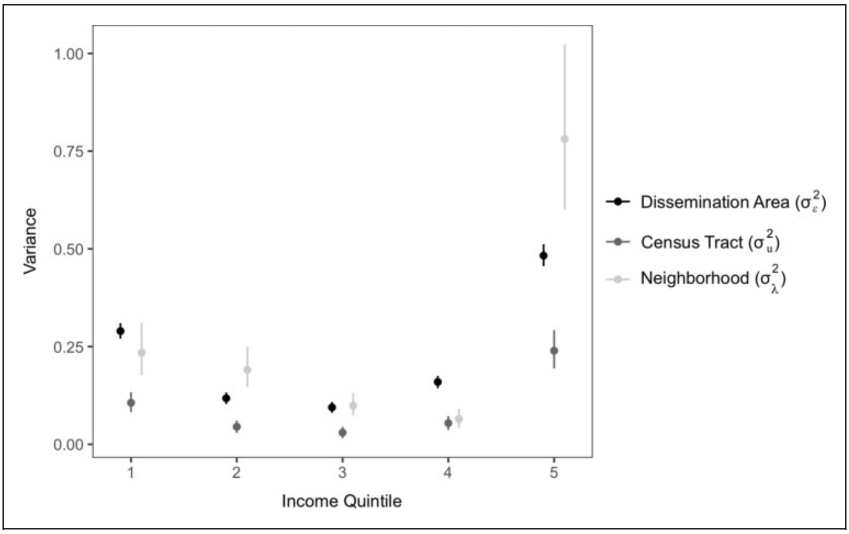

Figure 2. Global income segregation at the micro- (dissemination area), meso- (census tract), and macro-scales (neighborhood) (Model 1). The posterior means are represented by points, and the 95% CIs are represented by vertical lines.

important than directly analyzing the three different neighborhood contexts in which income segregation was high or low. The WinBUGS code for Model 3 and the full results for Model 3 are shown in the Supplementary Materials (Figure S2 and Table S1).

Before exploring the results of Model 3, it is first instructive to review the global segregation patterns observed in Model 1 (Figure 2). For all three spatial scales, the most affluent families were found to have the highest levels of segregation, and the poorest families were found to have the second-highest levels of segregation. The separation of these income classes was particularly evident at the micro- and macro-scales. For the most affluent families, 52% (95% CI: 45%–59%)[5,6] and 32% (27%–37%) of the total global segregation was explained at the macro- and micro-scales, respectively; and for the poorest families, 38% (31%–45%) and 46% (41%–52%) of the total global segregation was explained at the macro- and micro-scales, respectively. While families in the second, third, and fourth income quintiles had similarly low levels of segregation for each scale, the macro- and micro-scales remained the most important, explaining 54% (47%–61%) and 35% (30%–41%) of the total global segregation for the second quintile; 43% (37%–50%) and 46% (40%–52%) of the total global segregation for the third quintile; and 21% (15%–28%) and 61% (56%–66%) of the total global segregation for the fourth quintile.

Table 3. Posterior means and 95% CIs (in parentheses) for the regression coefficients describing the patterns of income and income segregation.

	City center	Subway accessibility	NIA
Income (β)			
First quintile	0.07 (–0.12, 0.26)	0.01 (–0.15, 0.19)	0.57 (0.36, 0.78)
Second quintile	–0.25 (–0.39, –0.12)	–0.15 (–0.27, –0.03)	0.45 (0.31, 0.60)
Third quintile	–0.18 (–0.27, –0.08)	–0.16 (–0.25, –0.07)	0.16 (0.05, 0.27)
Fourth quintile	–0.06 (–0.14, 0.03)	–0.17 (–0.25, –0.10)	–0.21 (–0.31, –0.10)
Fifth quintile	0.33 (0.06, 0.63)	0.26 (–0.03, 0.52)	–1.30 (–1.62, –1.01)
Income segregation (γ)			
First quintile	–0.15 (–0.39, 0.11)	0.13 (–0.07, 0.36)	0.41 (–0.17, 0.67)
Second quintile	–0.27 (–0.54, –0.01)	0.31 (0.06, 0.56)	–0.46 (–0.76, –0.16)
Third quintile	–0.10 (–0.35, 0.13)	0.31 (0.07, 0.54)	0.34 (0.06, 0.61)
Fourth quintile	–0.38 (–0.63, –0.13)	0.18 (–0.08, 0.40)	1.20 (0.90, 1.48)
Fifth quintile	–0.30 (–0.58, –0.02)	0.20 (–0.03, 0.45)	0.68 (0.38, 0.95)

NIA: neighborhood improvement area. Coefficient estimates greater (less) than zero indicate a positive (negative) association between the explanatory variable and income or income segregation.

Local patterns of income segregation

Table 3 displays the results of the regression coefficients in Model 3 that described the macro-scale patterns of both income and income segregation. Focusing first on income, higher proportions of the poorest families were found to live in NIAs than in non-NIA neighborhoods and smaller proportions of middle-income families (second, third, and fourth quintiles) were found to live in the city center and in neighborhoods with subway accessibility compared to inner suburban neighborhoods and areas not serviced by the subway. The proportion of the most affluent families was found to be positively associated with location in the city center and negatively associated with NIA status. The results of the city center coefficients, in particular, support visual interpretation of Figure 1 indicating that central areas of Toronto had high proportions of the most affluent families at the exclusion almost all other income groups.

Focusing on the local patterns of income segregation, the poorest families were not found to have significantly higher or lower levels of segregation (at 95% CI) in any of the macro-scale contexts analyzed in this study. Families in the fourth and fifth quintiles, in contrast, had lower levels of segregation in the city center and higher levels of segregation within NIAs, suggesting that the highest-income families had a relatively even distribution within the city center but were highly clustered in specific DAs within NIAs. Families in the second, third, and fourth quintiles had relatively similar coefficient estimates for the city center and subway accessibility, with lower levels of segregation in the city center but higher levels of segregation in areas serviced by the subway. Within NIAs, however, families in the second quintile were more evenly distributed than in non-NIA neighborhoods, whereas families in the third and fourth quintiles were more segregated in NIAs than in non-NIA neighborhoods.

The local micro-scale segregation estimates from Model 3 are mapped in Figure 3. The most affluent families were found to have the strongest local patterning of segregation, with micro-scale estimates of $\sigma^2_{\epsilon_{ijk5}}$ ranging from 0.07 to 7.57 in Model 3 compared to a global micro-scale segregation of $\sigma^2_{\epsilon_5} = 0.52$ (0.49–0.55) in Model 1. The fourth quintile also had strong local patterning of segregation relative to the global estimate ($\sigma^2_{\epsilon_{ijk4}}$ ranging from 0.02 to 1.94 in Model 3 compared to $\sigma^2_{\epsilon_4} = 0.16$ (0.15–0.17) in Model 1); however, the most

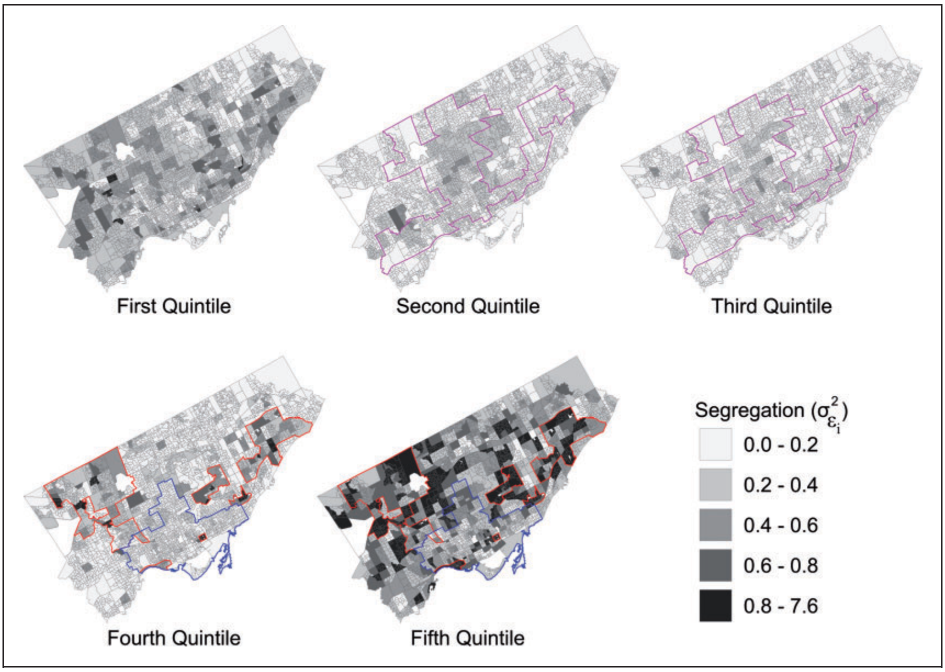

Figure 3. Local micro-scale segregation estimates from Model 3. The city center is outlined in blue, NIAs are outlined in red, and subway-accessible neighborhoods are outlined in magenta.

affluent families were shown to be highly segregated among large contiguous groups of DAs, whereas families in the fourth quintile were highly segregated among a small number of DAs located primarily in the east and northwest. While families in the lower three quintiles had relatively weaker local segregation patterns than the two highest-income classes, there were still substantial local variations not captured in the global model; micro-scale segregation estimates ranged from 0.07 to 1.01 for the first quintile (compared to 0.30 (0.29–0.32) in Model 1); 0.04 to 0.62 for the second quintile (compared to 0.12 (0.11–0.13) in Model 1); and 0.03 to 0.58 for the third quintile (compared to 0.09 (0.08–0.11) in Model 1).

Discussion

This study has applied a multilevel multigroup modeling approach to examine the global and local patterns of income segregation at three spatial scales in Toronto, Canada. The global segregation model, which assumed that each income quintile had constant scale-specific levels of segregation, showed that income segregation was largely driven by the separation of the most affluent and the poorest families at the macro- and micro-scales. This broadly supports contemporary research observing that income segregation in many American and Canadian cities is characterized by the sorting of both affluence and poverty away from the middle-class rather than the separation of lower-income families away from all other income groups (Massey and Eggers, 1993; Reardon and Bischoff, 2011; Walks and Maaranen, 2008). The local segregation model, which allowed the micro-scale segregation estimates to geographically vary according to macro-scale covariates and latent random effect terms, found that higher-income families had lower levels of segregation in the city center than in the inner suburbs, that middle-income families had high levels of segregation in areas with subway accessibility, and that almost all income classes had high levels of segregation in NIAs. Visual exploration of the local micro-scale segregation estimates supports the model fit statistics indicating that there were substantial local patterns of segregation otherwise overlooked by the global models, particularly among families in the highest-income quintiles.

By integrating the place-based focus of local index-based methods within the multilevel modeling frameworks employed in multiscale segregation research, this study advances the analysis of urban segregation in two ways. First, the local segregation models employed in this study produce area-specific segregation estimates after accounting for global segregation at the macro- and meso-scales, whereas local index-based methods accommodate data measured at only one scale and may produce area-specific segregation estimates that are confounded by stronger patterns of segregation among higher-level units of analysis (i.e. macro- or meso-scales if local segregation is analyzed at the micro-scale) (Jones et al., 2018). Second, the models in this study estimate micro-scale segregation as a function of observed covariates, which help to describe the contexts in which segregation is particularly high or low, and latent random effect terms, which allow for the local micro-scale segregation estimates to be clustered within both meso- and macro-areas. In contrast, interpretation of local segregation indices relies on visual observation of maps and so the degree to which segregation varies, as well as the contexts in which segregation is particularly high or low, is not assessed.

Enabled by these methodological advances, this study provides a more comprehensive picture of income segregation than past research focused on the separation of low-income residents at one spatial scale. For example, this study finds that, compared to the inner suburbs, the city center was characterized by higher proportions of the highest-income families and smaller proportions of lower-middle and middle-income families, as well as lower levels of segregation among both high- and low-income families. One explanation for this finding may be that city center neighborhoods are composed of heterogeneous micro-areas that have historic dwellings and newly developed condominiums typically occupied by higher-income families as well as multifamily rental and social housing units typically occupied by lower-income families (Rosen and Walks, 2015; Skaburskis and Nelson, 2014). In contrast, the inner suburbs in Toronto are generally composed of homogenous micro-areas that have only single-detached dwellings typically occupied by middle-income families or only high-rise apartments typically home to lower-income families.

This study also found that neighborhoods accessible by the subway had higher proportions of high-income families (although not significant at 95% CI; Table 3), smaller proportions of families in the middle three income quintiles, and higher levels of segregation among these middle-income families compared to areas inaccessible by the subway. This supports and extends past research highlighting the links between the subway, gentrification, and increasing concentrations of affluence (Grube-Cavers and Patterson, 2015; Hulchanski, 2010) by showing that, to the limited degree that middle-income families lived in these contexts, they were significantly clustered within micro-areas. This local segregation pattern may be explained by a confluence of two processes unique to neighborhoods near to the subway: the replacement of middle-class dwellings with transit-oriented residential developments largely targeted toward higher-income residents and a lack of single-detached housing that is affordable for middle-income families.

Finally, the results of this study show that NIAs had higher proportions of lower-income families in the first, second, and third income quintiles and smaller proportions of higher-income families in the fourth and fifth quintiles than non-NIA neighborhoods. This is expected, as the proportion of low-income families is one of several criteria used by the

City of Toronto to define NIAs. However, only families in the second quintile were less segregated in these contexts, which points to a clustering of the poorest families within NIAs, an even distribution of lower-middle income families within NIAs, and a clustering of higher-income families within NIAs. Combined, the local segregation patterns observed in the city center and in NIAs suggests there may be different processes of segregation present in low-income places (i.e. clustering of both high- and low-income families in NIAs) and in high-income places (i.e. even distribution of high- and low-income families in the city center).

Limitations and future research

One limitation of this study is that the local models assume that the micro-scale segregation estimates are correlated within meso- and macro-areas but not between nearby areas at any scale. This contrasts with local index-based methods that impose spatial autocorrelation by using distance or adjacency information to create subsets of areas for which segregation is calculated (Feitosa et al., 2007; O'Sullivan and Wong, 2007). Within the multilevel modeling framework, it may be possible to add spatially structured random effect terms that allow for the local patterns of income and segregation to be explained by latent components capturing spatial heterogeneity and spatial autocorrelation; however, researchers should be aware of the identifiability challenges associated with fitting multiple sets of random effect terms at multiple scales (Dong and Harris, 2015; Quick and Luan, 2020; Riebler et al., 2016). Second, the intersections between income and other characteristics shaping socio-spatial inequality were not considered in this study. Applying the segregation models developed in this study to compare the patterns exhibited by ethnic groups with various income levels would help to further understand the complexities of urban and intra-urban segregation. Third, the results of this study must be understood in context of the modifiable areal unit problem, as analyses using alternative spatial scales and/or zonal boundaries may have different findings than those presented here (Jones et al., 2018).

Future research may consider extending this modeling approach to explore segregation across multiple cities as well as multiple time periods. This would help to understand how segregation manifests among cities in the urban system (Townshend and Walker, 2002), the similarities or differences in segregation among intra-urban contexts, and how global and local segregation patterns have changed over time (Arcaya et al., 2018; Leckie and Goldstein, 2015). Further methodological development may consider the specification and estimation of mixture models, where segregation profiles (i.e. a mix of micro-, meso-, and macro-scale segregation) are estimated from the data and areas are assigned to one segregation profile. In developing more robust analyses of local segregation, it would be particularly informative to combine these modeling approaches with qualitative research into how and why various macro-, meso-, and micro-scale factors influence residential sorting for families across the income distribution, including locational characteristics, amenities, public services, and a variety of structural constraints.

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Data and code availability

The data and code for Model 3 is accessible at: https://figshare.com/s/95074b5fd33bc32b6805.

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Notes

1. Economic families are defined as a group of two or more persons who live in the same dwelling and are related by blood, marriage, or common-law union (Statistics Canada, 2019a). Income decile classification is based on the national distribution of after-tax income and is adjusted for household size (Statistics Canada, 2019b).
2. Prior to 1 June 1998, the present-day City of Toronto was composed of six separate municipalities: Toronto, East York, Etobicoke, North York, Scarborough, and York.
3. Of the 3702 DAs in the study region, 66 (= 1.78%) had missing income and population data and were excluded from analysis.
4. Following Brunton-Smith et al. (2020), numeric superscripts distinguish the random effect terms used to analyze the spatial patterns of income (1 in the model for π_{ijkq}) and the spatial patterns of income segregation (2 in the model for $\sigma^2_{\epsilon_{ijkq}}$).
5. Variance partition coefficients (VPCs) quantify the degree to which each scale explains the total global variance or segregation of the income quintiles (Browne et al., 2005; Goldstein et al., 2002). In Model 1, for example, the proportion of total global segregation attributed to the macro-scale is equal to $\sigma^2_{\lambda_q}/(\sigma^2_{\lambda_q} + \sigma^2_{u_q} + \sigma^2_{\epsilon_q})$). The VPCs were calculated at each MCMC iteration and are reported in this article via the posterior means and 95% credible intervals. For additional information regarding the differences between stochastic variation in the data and variation between DAs, CTs, and neighborhoods, see Jones et al. (2015; pp. 2000–2001).
6. The 95% credible interval (95% CI) is the interval that contains the true value of a parameter with 95% probability.

Supplemental material

Supplemental material for this article is available online.

References

Acevedo-Garcia D (2001) Zip code-level risk factors for tuberculosis: Neighborhood environment and residential segregation in New Jersey, 1985-1992. *American Journal of Public Health* 91(5): 734–741.

Ades J, Apparicio P and Seguin A-M (2012) Are new patterns of low-income distribution emerging in Canadian metropolitan areas. *The Canadian Geographer / Le Géographe Canadien* 56(3): 339–361.

Anselin L (1995) Local indicators of spatial association – LISA. *Geographical Analysis* 27(2): 93–115.

Arcaya MC, Schwartz G and Subramanian SV (2018) A multi-level modeling approach to understanding residential segregation in the United States. *Environment and Planning B: Urban Analytics and City Science* 45(6): 1090–1105.

Barros J and Feitosa FF (2018) Uneven geographies: Exploring the sensitivity of spatial indices of residential segregation. *Environment and Planning B: Urban Analytics and City Science* 45(6): 1073–1089.

Brooks SP and Gelman A (1998) General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics* 7(4): 434–455.

Brown LA and Chung S-Y (2006) Spatial segregation, segregation indices, and the geographical perspective. *Population, Space and Place* 12: 235–243.

Browne WJ, Subramanian WV, Jones K, et al. (2005) Variance portioning in multilevel logistic models that exhibit overdispersion. *Journal of the Royal Statistical Society Series A: Statistics in Society* 168(3): 588–613.

Brunton-Smith I, Pina-Sanchez J and Li G (2020) Re-assessing the consistency of sentencing decisions in cases of assault: Allowing for within-court inconsistencies. *The British Journal of Criminology*. Epub ahead of print 23 May 2020. DOI: 10.1093/bjc/azaa030.

Catney G (2018) The complex geographies of ethnic residential segregation: Using spatial and local measures to explore scale-dependency and spatial relationships. *Transactions of the Institute of British Geographers* 43: 137–152.

City of Toronto (2020) Neighbourhood profiles. Available at: https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/ (accessed 21 May 2020).

Dong G and Harris R (2015) Spatial autoregressive models for geographically hierarchical data structures. *Geographical Analysis* 47(2): 173–191.

Duncan OD and Duncan B (1955) A methodological analysis of segregation indexes. *American Sociological Review* 20(2): 210–217.

El-Geneidy A, Grimsrud M, Wasfi R, et al. (2014) New evidence on walking distances to transit stops: Identifying redundancies and gaps using variable service areas. *Transportation* 41(1): 193–210.

Feitosa FF, Camara G, Monteiro AMV, et al. (2007) Global and local spatial indices of urban segregation. *International Journal of Geographical Information Science* 21(3): 299–323.

Fong E and Shibuya K (2000) The spatial separation of the poor in Canadian cities. *Demography* 37(4): 449–459.

Fowler CS (2018) Key assumptions in multiscale segregation measures: How zoning and strength of spatial association condition outcomes. *Environment and Planning B: Urban Analytics and City Science* 45(6): 1055–1072.

Gelman A (2006) Prior distributions for variance parameters in hierarchical. *Bayesian Analysis* 1(3): 515–534.

Goldstein H, Browne W and Rasbash J (2002) Partitioning variation in multilevel models. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences* 1(4): 223–231.

Goldstein H and Noden P (2003) Modelling social segregation. *Oxford Review of Education* 29(2): 225–237.

Grube-Cavers A and Patterson Z (2015) Urban rapid rail transit and gentrification in Canadian urban centres: A survival analysis approach. *Urban Studies* 52(1): 178–194.

Harris R (2017) Measuring the scales of segregation: Looking at the residential separation of white British and other schoolchildren in England using a multilevel index of dissimilarity. *Transactions of the Institute of British Geographers* 42: 432–444.

Hulchanski JD (2010) *The Three Cities within Toronto: Income Polarization among Toronto's Neighbourhoods, 1970– 2005*. Toronto, ON: University of Toronto Cities Centre. Available at: http://www.urbancentre.utoronto.ca/pdfs/curp/tnrn/Three-Cities-Within-Toronto-2010-Final.pdf (accessed 2 September 2020).

Jargowsky PA (1996) Take the money and run: Economic segregation in U.S. metropolitan areas. *American Sociological Review* 61(6): 948–998.

Johnston R, Forrest J, Jones K, et al. (2016a) The scale of segregation: Ancestral groups in Sydney, 2011. *Urban Geography* 37(7): 985–1008.

Johnston R, Jones K, Manley D, et al. (2016b) Macro-scale stability and micro-scale diversity: Modelling changing ethnic minority residential segregation - London 2011–2011. *Transactions of the Institute of British Geographers* 41: 389–402.

Jones K, Johnston R, Manley D, et al. (2015) Ethnic residential segregation: A multilevel, multigroup, multiscale approach exemplified by London in 2011. *Demography* 52: 1995–2019.

Jones K, Manley D, Johnston R, et al. (2018) Modelling residential segregation as unevenness and clustering: A multilevel modelling approach including spatial dependence and tacking the MAUP. *Environment and Planning B: Urban Analytics and City Science* 45(6): 1122–1141.

Leckie G, French R, Charlton C, et al. (2014) Modeling heterogeneous variance-covariance components in two-level models. *Journal of Educational and Behavioral Statistics* 39(5): 307–332.
Leckie G and Goldstein H (2015) A multilevel modelling approach to measuring changing patterns of ethnic composition and segregation among London secondary schools, 2001–2010. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 178(2): 405–424.
Leckie G, Pillinger R, Jones K, et al. (2012) Multilevel modeling of social segregation. *Journal of Educational and Behavioral Statistics* 37(1): 3–30.
Lee Y and Nelder JA (2006) Double hierarchical generalized linear models (with discussion). *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 55(2): 139–185.
Lloyd CD and Shuttleworth I (2012) Residential segregation in Northern Ireland: Assessing the value of exploring spatial variation. *Environment and Planning A: Economy and Space* 44: 52–67.
Lunn D, Jackson C, Best N, et al. (2012) *The BUGS Book: A Practical Introduction to Bayesian Analysis*. London: Chapman and Hall/CRC Press.
Manley D, Johnston R, Jones K, et al. (2015) Macro-, meso-, and microscale segregation: Modeling changing ethnic residential patterns in Auckland, New Zealand, 2001–2013. *Annals of the Association of American Geographers* 105(5): 951–967.
Manley D, Jones K and Johnston R (2019) Multiscale segregation: Multilevel modeling of dissimilarity – Challenging the stylized fact that segregation is greater the finer the spatial scale. *The Professional Geographer* 71(3): 566–578.
Massey DS and Denton NA (1988) The dimensions of residential segregation. *Social Forces* 67(2): 281–315.
Massey DS and Eggers ML (1990) The ecology of inequality: Minorities and the concentration of poverty, 1970-1980. *American Journal of Sociology* 95(5): 1153–1188.
Massey DS and Eggers ML (1993) The spatial concentration of affluence and poverty during the 1970s. *Urban Affairs Quarterly* 29(2): 299–315.
Massey DS, Rothwell J and Domina T (2009) The changing bases of segregation in the United States. *The Annals of the American Academy of Political and Social Science* 626(1): 74–90.
Ontario Ministry of Transportation (2012) Transit supportive guidelines. Available at: http://www.mto.gov.on.ca/english/transit/pdfs/transit-supportive-guidelines.pdf (accessed 22 June 2020).
O'Sullivan D and Wong DWS (2007) A surface-based approach to measuring spatial segregation. *Geographical Analysis* 39: 147–168.
Owens A (2018) Income segregation between school districts and inequality in student's achievement. *Sociology of Education* 91(1): 1–27.
Petrovic A, van Ham M and Manley D (2018) Multiscale measures of population: Within- and between-city variation in exposure to the sociospatial context. *Annals of the American Association of Geographers* 108(4): 1057–1074.
Quick M and Luan H (2020) The spatial structure of socioeconomic disadvantage: A Bayesian multivariate spatial factor analysis. *International Journal of Geographical Information Science*. Epub ahead of print 7 May 2020. DOI: 10.1080/13658816.2020.1759807.
Reardon SF (2006) A conceptual framework for measuring segregation and its association with population outcomes. In: Oakes JM and Kaufman JS (eds) *Methods in Social Epidemiology*. San Francisco: Jossey-Bass, pp.169–192.
Reardon SF and Bischoff K (2011) Income inequality and income segregation. *American Journal of Sociology* 116(4): 1092–1153.
Reardon SF, Matthews SA, O'Sullivan D, et al. (2008) The geographic scale of metropolitan racial segregation. *Demography* 45(3): 489–514.
Reardon SF and O'Sullivan D (2004) Measures of spatial segregation. *Sociological Methodology* 34(1): 121–162.
Riebler A, Sorybye SH, Simpson D, et al. (2016) An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research* 25(4): 1145–1165.
Roberto E (2018) The spatial proximity and connectivity method for measuring and analyzing residential segregation. *Sociological Methodology* 48(1): 182–224.
Rosen G and Walks A (2015) Castles in Toronto's sky: Condo-ism as urban transformation. *Journal of Urban Affairs* 37(3): 289–310.

Ross NA, Houle C, Dunn JR, et al. (2004) Dimensions and dynamics of residential segregation by income in urban Canada, 1991–1996. *The Canadian Geographer/ Le Géographe Canadien* 48(4): 433–445.
Ross NA, Nobrega K and Dunn J (2001) Income segregation, income inequality and mortality in North American metropolitan areas. *GeoJournal* 53: 117–124.
Sakoda JM (1981) A generalized index of dissimilarity. *Demography* 18: 245–250.
Skaburskis A and Nelson K (2014) Filtering and gentrifying in Toronto: Neighbourhood transitions in and out from the lowest income decline between 1981 and 2006. *Environment and Planning A: Economy and Space* 46: 885–900.
Slater T (2013) Your life chances affect where you live: A critique of the 'cottage industry' of neighbourhood effects research. *International Journal of Urban and Regional Research* 37(2): 367–387.
Spiegelhalter DJ, Best NG, Carlin BP, et al. (2002) Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64(4): 583–639.
Statistics Canada (2019a) Economic family structure of economic family. Available at: https://www23.statcan.gc.ca/imdb/p3Var.pl?Function = DEC&Id = 238685 (accessed 21 May 2020).
Statistics Canada (2019b) Adjusted after-tax income of private household. Available at https://www23.statcan.gc.ca/imdb/p3Var.pl?Function = DEC&Id = 252252 (accessed 21 May 2020).
Statistics Canada (2020) Upper income limit, income share and average of adjusted market, total and after-tax income by income decile. Available at: https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid = 1110019301 (accessed 13 May 2020).
Townshend IJ and Walker R (2002) The structure of income residential segregation in Canadian metropolitan areas. *Canadian Journal of Regional Science Spring* 25(1): 25–52.
Walks RA and Maaranen R (2008) Gentrification, social mix, and social polarization: Testing the linkages in large Canadian cities. *Urban Geography* 29(4): 293–326.
Winship C (1977) A revaluation of indexes of residential segregation. *Social Forces* 55(4): 1058–1066.
Wong DS (2003) Spatial decomposition of segregation indices: A framework toward measuring segregation at multiple levels. *Geographical Analysis* 35(3): 179–194.
Wong DWS (2002) Modeling local segregation: A spatial interaction approach. *Geographical and Environmental Modelling* 6(1): 81–97.
Yao J, Wong DWS, Bailey N, et al. (2018) Spatial segregation measures: A methodological review. *Tijdschrift Voor Economische en Sociale Geografie* 110(3): 235–250.

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