The Canadian Geographer
Le Géographe canadien
Canadian Association of Geographers
Association Canadienne des Géographes

The power of a simple index of neighbourhood change: Challenging the perception that there is no such thing as simplicity in creating indexes

Howard Ramos
Department of Sociology, Western University

Lisa Kaida
Department of Sociology, McMaster University

Diana Singh
Department of Sociology, McMaster University

Paul Pritchard
Department of Sociology, University of Toronto

Rochelle Wijesingha
Ontario Secondary School Teacher's Federation

Key Messages

- We develop two "simple" indexes of neighbourhood change that can be easily used by urban planners and NGOs, as well as students and intermediate academic researchers.
- The simple indexes consider three dimensions of neighbourhood change: economic, sociocultural, and physical dimensions.
- There is a power to a simple approach to understanding neighbourhood change.

While academic research on neighbourhood change has developed over the past 30 years, its measurement is often technical and complex, hampering knowledge translation of academic research to wider audiences. Based on our research on neighbourhood change in Atlantic Canadian cities, we have developed two "simple" indexes of neighbourhood change. We document the steps to creating the simple indexes and discuss what decisions are made along the way. We then compare results of the two indexes with a mean-centred index that is commonly used for academic audiences. This is done to assess how simpler methods perform compared to one that is considered more sophisticated. Using the 2006 and 2016 Canadian Census data, we apply each of these neighbourhood change indexes to four Atlantic Canadian cities. Results indicate some similarities between the simple indexes and the mean-centred index. We discuss the methodological and practical implications of the results to help facilitate knowledge translation of academic research for urban planners and NGOs.

Keywords: neighbourhood change, neighbourhood index, Atlantic Canada, Census

Correspondence to / Adresse de correspondance: Lisa Kaida, Department of Sociology, McMaster University, 1280 Main St. W., Hamilton, ON L8S 4M4.
Email/Courriel: kaidar@mcmaster.ca

DOI: 10.1111/cag.12711

Le pouvoir d'un indice de transformation des quartiers : favoriser la simplicité dans la création d'indices comparatifs

Bien que la recherche universitaire sur l'évolution sociodémographique des quartiers se soit développée au cours des 30 dernières années, les mesures utilisées sont souvent complexes, ce qui entrave la diffusion des connaissances issues de la recherche universitaire. À partir de nos recherches sur les transformations des quartiers dans les villes du Canada atlantique, nous avons élaboré deux indices « simples » afin de mesurer le changement. Nous documentons ici les étapes de la création de ces indices simples, notamment en ce qui concerne les décisions méthodologiques prises durant ce processus. Nous comparons ensuite les résultats de ces deux indices avec un indice complexe centré sur la moyenne, indice qui est couramment utilisé par les universitaires. Cela permet d'évaluer la performance des méthodes plus simples par rapport aux méthodes jugées plus sophistiquées. À l'aide des données des recensements canadiens de 2006 et 2016, nous testons alors chacun des indices de transformation des quartiers à quatre villes du Canada atlantique. Les résultats indiquent certaines similitudes entre les indices simples et l'indice centré sur la moyenne. Pour finir, nous évaluons les implications méthodologiques et pratiques des résultats afin de faciliter l'utilisation des connaissances scientifiques par les gestionnaires, les urbanistes et les ONG.

Mots clés : transformation des quartiers, indice de classement des quartiers, Canada atlantique, Recensement

Introduction

Academic researchers are increasingly constructing neighbourhood indexes to assess urban change. Since 2000, about 180 studies have used a neighbourhood index across a diverse range of peer-reviewed journals such as *The Canadian Geographer, Housing Studies, Housing Policy Debate, Social Forces, Urban Affairs Review*, and *Urban Studies* (e.g., Van Criekingen and Decroly 2003; Swaroop and Morenoff 2006; Walks 2007; Jun 2013; Jackson 2015; Jones and Ley 2016). Researchers from different disciplinary backgrounds, including geography, urban studies, sociology, and economics, have used neighbourhood indexes to measure economic, socio-cultural, and physical dimensions of change in neighbourhoods. Much of the focus is on how neighbourhoods change over time, and many examine processes of gentrification, deindustrialization, and urban decay (e.g., Meligrana and Skaburskis 2005; Vigdor 2010; Andersson and Turner 2014).

Despite such widespread use of indexes in academia to capture properties of neighbourhoods and changes in them, the impact of indexes on applied urban planning, community development, or municipal policy are often hampered by the technical literacy needed to interpret them. Academic indexes measuring neighbourhood change often require advanced statistical training to analyze data that cannot be publicly accessed and can be difficult to understand for those working on the ground in communities. We have observed through our work on the perception of changes in Atlantic Canadian cities that local community organizations (e.g., United Way Halifax, Immigrant Services Association of Nova Scotia, Halifax Partnership, Engage NS) have an appetite for straightforward and accessible research methods based on readily available data. For these reasons, in this paper, we provide steps to creating a simple index using publicly accessible data and then assess how different constructions of indexes of neighbourhood change perform.

We compare the performance of two simple indexes against a more methodologically rigorous method. Our main goal is to help demonstrate the considerations that one must make in constructing neighbourhood change indexes across multiple dimensions using a number of variables. To do this, we introduce three indexes of neighbourhood change. These include two simple indexes that are straightforward and uncomplicated to construct using publicly available neighbourhood data and basic spreadsheet software (e.g., Excel), and do not involve much calculation beyond addition and division. We also introduce a third index that uses a mean-centred method, which is commonly adopted by academic researchers, and assess how the two simple indexes perform against it (Kaida, Ramos, Singh, Pritchard et al. 2020).

This paper begins by examining existing research on neighbourhood change to identify which dimensions of change are most commonly studied and how they are measured. We then explain how to create the three indexes of neighbourhood change. We apply the indexes to four medium-size Atlantic

Canadian cities—Halifax (Nova Scotia), St. John's (Newfoundland and Labrador), Moncton (New Brunswick), and Charlottetown (Prince Edward Island)—to assess neighbourhood change and compare how the three indexes perform using descriptive statistics and multivariate analyses. In so doing, we analyze neighbourhoods across the four cities and identify which have experienced the most overall change and the neighbourhood characteristics that contribute the most to overall change in different neighbourhoods. We summarize the findings and conclude by discussing strengths and weaknesses of the three indexes and how they can be used by urban planners and non-governmental organizations (NGOs). Non-specialists, students, and intermediate academic researchers can also benefit from our investigation of simple indexes that do not require complex statistical procedures.

Academic research on neighbourhood change and limitations for its knowledge translation

Researchers have used various focal lenses to capture and explain neighbourhood change. One of the most common areas of focus has been on the process of gentrification (Hamnett 1991; Melingrana and Skaburskis 2005; Walks and Maaranen 2008; Lees et al. 2013). As a more established area of research, the gentrification literature is vast, and "change" examined in this context is less neutral than in other areas of neighbourhood change research. We note this as a cautionary point and emphasize that change can have both positive and negative outcomes and that the first step to identifying either is to be able to pinpoint where the greatest changes are occurring.

Researchers looking at gentrification as well as neighbourhood change generally adopt one of two main approaches. On the one hand, some researchers take a descriptive approach and explore how a neighbourhood or certain neighbourhoods within a city have changed over time. They often focus on the demographic and socio-economic trends associated with these changes, such as changes in income distribution or ethnoracial composition—or structural revitalization and changes to land use associated with physical urban renewal as well as social capital (e.g., Meegan and Mitchel 2001; Steinmetz-Wood et al. 2017). On the other hand, other researchers adopt an explanatory approach to investigating the determinants of neighbourhood change, asking what factors drive gentrification (e.g., Meegan and Mitchell 2001; Jun 2013).

There is also much discussion in urban studies about the challenges associated with developing a typology of neighbourhood change (Van Criekingen and Decroly 2002). Ruth Glass's original conceptualization of gentrification (Centre of Urban Studies 1964), for instance, primarily focused on economic stratification and other socio-economic markers (e.g., income, housing values, education)—see MacDonald and Stokes (2020) for a recent review. Other researchers argue the determinants of neighbourhood change should include a broad range of factors, such as macroeconomic trends (e.g., unemployment rates), spatial segregation through residents' self-selection into certain neighbourhoods based on their racial preferences, quality of neighbourhoods pertaining to housing conditions, and community cohesion (Meegan and Mitchell 2001; Jun 2013). Other work has focused on developing and expanding pre-existing models of the determinants of neighbourhood change. Rosenthal (2008), for example, discusses how some existing models of neighbourhood change include important indicators of short- and long-term neighbourhood economic status, such as the age and physical condition of homes and the demographic and socio-economic compositions of residents (e.g., average income).

The relationship between race and neighbourhood change is also a source of considerable attention in the literature (Hwang 2020). While Canadian studies on this topic are limited, studies in the United States (US) tend to focus on racial preference and residential segregation because of the concentration of ethnic minorities living in older, low income neighbourhoods susceptible to gentrification (Brown-Saracino 2017). Some studies in the 1980s and early 1990s revealed that white residents preferred not to live in predominantly black neighbourhoods, resulting in greater racial residential segregation (Frey and Farley 1996; Logan and Zhang 2010). More recent research finds white "gentrifiers" are more inclined to choose ethnically diverse neighbourhoods because of the culture and authenticity (e.g., Brown-Saracino 2009; Nevarez and Simons 2020).

The literature on the determinants of neighbourhood cycles of decline and renewal tend to focus on a small number of key determinants of change. These fall within the realm of the economic, sociocultural, and physical dimensions of neighbourhoods. Some Canadian research on neighbourhood change, for example, has focused on social status and sociodemographic dimensions (Ley 1994; Ley and Dobson 2008), while others have expanded their analyses of changing neighbourhoods to include measures of average rent and income and dwelling unit density (Meligrana and Skaburskis 2005). Despite little consensus over the definition of processes of neighbourhood change, including gentrification, David Ley's (1987, 1994) gentrification index is often cited in Canadian research. The index is a validated measure of neighbourhood socio-economic status and operationalizes gentrification in terms of social status, including measures of professional-managerial employment and the percentage of residents with post-secondary education across Census Tracts (CTs). Other researchers have expanded upon this measure, recognizing change occurs more holistically, and include analyses of economic (e.g., average rent) and physical dimensions of change, in addition to socio-economic and demographic change (Meligrana and Skaburskis 2005; Eckerd 2011). Similarly, to establish a typology of neighbourhood renewal, Van Criekingen and Decroly (2003) identify three main criteria for determining neighbourhood transformation, including improvements to the built environment, growth in social status, and population change.

Methodologically, there are a number of different approaches to constructing measures of neighbourhood change. To effectively capture neighbourhood change, most researchers use an index or a multistage process of analyses (e.g., Meegan and Mitchell 2001; Ley and Dobson 2008; Kaida, Ramos, Singh, Pritchard et al. 2020). For example, Meligrana and Skaburskis (2005) use CT data to calculate changes to income and rent over time across 10 Canadian cities, coupled with reports from local market analysts, to determine the location of changing neighbourhoods. Other researchers construct indexes based on select indicators of change. The gentrification index, for example, is a validated measure composed of two indicators of social status—the percentage of the population (aged 25 and older) with a college education and the percentage of the population working in the managerial and professional positions (Ley 1987 1994). These two percentages are added together and averaged across neighbourhoods over two time periods (e.g., 2000 and 2010). Similarly, measures such as the index of deprivation (Meegan and Mitchell 2001) and the social standing index (Van Criekingen and Decroly 2003) are calculated by combining variables such as unemployment rates, the percentage of households without a car, and levels of education, and then standardizing and summing each to construct a composite measure. In some instances, researchers employ more advanced statistical techniques on a set of neighbourhood characteristics, such as principal component analysis (PCA). In these studies, factor analyses are used to determine the extent to which a set of observed variables account for variation in broader unobserved neighbourhood processes such as socio-economic deprivation or gentrification (Meligrana and Skaburskis 2005; William and Morrison 2012).

Despite significant methodological advancements in the academic literature on neighbourhood change, knowledge translation at the local community level is often met with a number of challenges. From our experience, for example, local NGOs and urban planners often search for a single number or index that speaks to change in a given neighbourhood. Examples of this include: the Halifax Index, created by the Halifax Partnership, which represents the local business community; United Way's Neighbourhood Vitality Index; and the Neighbourhood Equity Index developed for the City of Ottawa (Meagher 2010; Halifax Partnership 2019; Social Planning Council of Ottawa 2019). If the index is not easily interpreted, its value is often questioned. The same challenge occurs if the data used in the index cannot be publicly accessed. Both issues disempower users and communities as they need to rely on outside experts for the interpretation and construction of an index. This is especially the case for indexes that use factor analysis or PCA in their construction, as they may create categories of change that do not seem mutually exclusive to non-specialists. Similarly, indexes that use more complex mathematical operations, which for example cannot be interpreted through simple increases or decreases in values, are difficult to interpret and require more detailed explanations of change.

These challenges are often rooted in fundamental divisions that exist across research interests, analyses, and sectors. That is, the objectives at each end of the community-academic spectrum produces distinct differences in terms of research focus, methodology, and rationale. While academic research is incentivized by knowledge production and contribution to a specific area of research, it is also driven by scientific rigour, sometimes including complex methodological approaches exclusive to an academic audience. For example, academic research on neighbourhood change tends to adopt advanced statistical methods which require highly specialized training and practice. The result, however, is a disconnect between academic research and its practical use, including the exchange of knowledge between researchers, urban planners, and NGOs.

How might these differences be reconciled? This conversation is not a new one. One of the ways in which knowledge mobilization and transfer can occur is through community-based research initiatives (Neighbourhood Change Research Partnership 2021). These types of collaborations between academics and community organizations have the potential to advance scholarly knowledge while also producing outputs that are directly relevant and practical to knowledge users. Urban planners, NGOs, and community members need to be equipped with the tools and information that help inform evidence-based decision making with regards to urban planning projects and policy development. Of particular importance is transferring knowledge that affects cities and neighbourhoods. The dissemination of data, methodologies, and research findings should be constructed in a way that can be used and understood by the general public. This paper argues to help facilitate the application of collaborative research, a simple but comprehensive measure of neighbourhood change is needed. We consider three dimensions of neighbourhood changes, economic, sociocultural, and physical changes to the built environment, following existing literature (e.g., Hammel and Wyly 1996; Atkinson 2000).

Methodology

Measurement of neighbourhood

The definitions of neighbourhood, and the dimensions associated with it, vary widely between studies (e.g., Baxter 2010; Mok 2010; Meltzer and Schuetz 2012) and mean vastly different things to people on the ground (Lee and Campbell 1997; Germain and Gagnon 1999), which thus warrants some discussion. Most studies recognize a neighbourhood as a social and geographic concept, composed of physical, symbolic, and subjective boundaries (Galster 2001; Coulton et al. 2013). While researchers offer many contrasting definitions, a common measure of neighbourhoods among those employing quantitative research designs are CTs (e.g., Walks 2001; Nicotera 2007; Kitchen and Williams 2009). Some criticize the usefulness of CTs as a proxy of neighbourhood because they can mask differences seen within them (Prouse et al. 2014). Meanwhile, others warn CTs do not work well for smaller cities because CT boundaries change over time (Kaida, Ramos, Singh, and McLay 2020), yet others argue objective or administrative neighbourhood boundaries are not always meaningful or consistent among those living in communities (Lee and Campbell 1997; Germain and Gagnon 1999). Nevertheless, CTs are widely used in urban studies because they are readily available, more stable than many of the alternative geographic measures, and data tend to be publicly available at this administrative level of geography.

Following this common approach, we used CTs in our analysis of neighbourhood change for Halifax, St. John's, and Moncton. For Charlottetown, we used Census Subdivisions (CSD), which represent a larger geographic area than CTs and are deemed equivalent to a municipality. CTs are available only for larger cities classified as CMAs (Census Metropolitan Areas) and some CAs (Census Agglomerations), and Charlottetown is an untracted CA. We interchangeably use "neighbourhoods" and "CTs" (and/or CSDs) throughout the paper.

Census data also contain a lower geography—the Dissemination Area (DA)—which could be used as an alternative neighbourhood unit. However, as discussed in Kaida, Ramos, Singh, and McLay (2020), changes in DA boundaries between census years are substantial, making it impossible to measure characteristics of the same areas at two time points using publicly available data.

Data

We obtained CT-/CSD-level data on economic, sociocultural, and physical characteristics in 2006 and 2016 using the Canadian Census Analyser, available through the University of Toronto Computing in the Humanities and Social Sciences (CHASS 2015). The Census Analyser is accessible to faculty, students, and staff in over 55 universities in Canada and the US who are participating in the Data Liberation Initiative. Aggregated census data are also available to anyone for free through the Government of Canada open data portal (Government of Canada 2021).

Construction of simple indexes

The point of creating an index is to collapse multiple dimensions and indicators into a single measure. There are many ways to do this. A common way of choosing indicators is to use factor analysis to identify which measures align with common dimensions. However, this requires statistical training, and from our experience of working with urban planners and NGOs, we find this approach can be inaccessible to many. Another approach is to select factors that are commonly used in policy or academic literature and are meaningful to those who are working in communities. That is, we select indicators that are theoretically or policy relevant. Atkinson (2000) and Hammel and Wyly (1996) note economic, sociocultural, and physical changes to the built environment are such dimensions of change, and our review confirmed they are consistently used in neighbourhood research. For this reason, we considered economic, sociocultural, and physical dimensions in construction of our simple indexes of neighbourhood change. A balanced number of measures in each dimension assures no single dimension skews the index.

For the economic dimension, we included the percentage of lone parent families, the percentage of low income households (renter households spending more than 30% of their income on housing), average income (at the individual level), and unemployment rates of CTs (or CSDs). We selected four indicators from the sociocultural dimension—the percentage of the population aged 65 and older, the percentage of the population who are immigrants, the percentage of the population who are visible minorities, and the percentage of the population with a bachelor's degree or higher in a CT (or a CSD). Finally, the physical dimension includes the percentage of occupied private dwellings that are apartments, the percentage of households who are renters/tenants, the percentage of one-person households, and the percentage of dwellings in need of major repairs. We calculated the percentages by simply dividing the total value of each variable by the total population who responded to the corresponding question on the Census questionnaire for a given CT (or CSD) and then multiplied by 100. Average incomes (in dollars) and unemployment rates do not require such conversion.

Once we selected the unit of analysis (CT or CSD), dimensions (economic, sociocultural, and physical), specific indicators for each dimension, and datasets (the 2006 and 2016 Censuses), the next set of decisions revolved around calculating an index itself. We propose two simple indexes for the general public.

Our first simple index (v1) considers absolute raw change within a neighbourhood over time. Using 2006 and 2016 Census data, we constructed this index by subtracting the value of the aforementioned 12 indicators (e.g., percentage of lone parent families) in 2006 from its value in 2016.

To demonstrate the calculation process more explicitly, we use an example from Halifax. If the percentage of total lone parent families in CT 113 in Halifax was 32% in 2006 and 6% in 2016, then a raw change value would be -26 (= 6-32). However, in our calculation of v1, we used the absolute value of change. This means we ignored the direction of change (+/-), resulting in a value of 26 for change in the percentage of lone parent families in the Halifax CT 113. We chose this method because as we discuss in the next step, we rank-ordered CTs according to changes for each measure. One of the main issues with using raw values is that ranking with negative values would result in a misrepresentation of overall change (i.e., negative values would be considered as less change than positive values). Therefore, we ranked absolute values across CTs for each city from the most to least changes, with a rank of 1 indicating the most changed CT.

Our choice of ranking serves two functions. First, it creates a common standardized score across different measures. This is important as it prevents measures that have very high or low fluctuation from unduly skewing the index. While this ranking method is less precise, it does offer a general picture of change. Second, it allows different types of measures to be combined to create a single score, which is the primary goal of an index. Continuing with the previous hypothetical example, let us suppose the Halifax CT 113 experienced the largest change in the proportion of lone parent families between 2006 and 2016, then this CT would receive a ranked score of 1. In other words, we reverse-ranked the highest values of change to equal 1. Conversely, if CT 26 in Halifax experienced the least change in its percentage of lone parent families, it would receive a ranked score of 86 as there are 86 CTs in Halifax in our analysis.

After this calculation was performed for all 12 neighbourhood measures, the ranked scores for all the 12 measures were then summed, producing an absolute raw change index score, which we call the simple index (v1). CTs were then sorted into quintiles based on the index values, where the top quintile represents the 20% most changed neighbourhoods. By looking at quintiles, we smoothed differences in rankings between CTs, rather than relying on individual scores. The processes are summarized in the following equation:

$$\textbf{Simple index score}(\mathbf{v}1) = \sum\left(- \mathbf{1}{*}\mathit{rank}|\mathbf{CT}_{t_2}\text{–}\mathbf{CT}_{t_1}|\right)$$

In this equation, t_1 refers to an earlier time point (e.g., 2006), whereas t_2 refers to the later time point (e.g., 2016).

Although this application allows one to see how much a neighbourhood changes, it has two limitations. First, by creating an absolute value to calculate the most and least change, we lose the ability to speak of whether or not change increases or decreases for a measure. Second, even if a CT has the most change on the index score or a specific measure, it does not mean its position vis-à-vis other neighbourhoods has changed. This is because a CT may be so far below the rest of the distribution or above it that even with the most change its position compared to other neighbourhoods may be negligible.

For these reasons, we created a relative simple index (v2) as well to consider how a neighbourhood experiences change in relation to other neighbourhoods in each city. We used the same 12 indicators of neighbourhood characteristics but calculated the index in a slightly different way. We first ranked CTs by their value for each measure for 2006 and 2016 separately. The highest value of a given measure is ranked 1, followed by other ranks to a maximum, which is the total number of CTs for each city. Again, to accomplish this, we reverse ranked to standardize across measures. In cases where CTs share the same values, they share the same rank. For example, if Halifax CT 10 had the highest percentage of lone parent families of all Halifax CTs in 2006, it would receive a ranked score of 1. If CT 113, on the other hand, had the lowest percentage of lone parent families of all CTs in the same year, and there were no tied ranks, this CT would receive a ranked score of 86. Ranks were then summed for each year, 2006 and 2016, which allowed us to create index scores for each year.

To analyze the relative change for each CT, we subtracted the 2006 index score from that of 2016. For example, if the 2006 index score for the Halifax CT 113 is 653 and the 2016 index score is 409, we calculated a difference between the 2006 and 2016 scores: –244 (= 409–653). Again, to gauge magnitude of change, we used an absolute value calculation for the same reasons as the first application of the simple index (v1). Those scores were then reverse ranked so the CT with the highest score was ranked 1, indicating the most change. The relative simple index scores were then categorized into quintiles.

The process is summarized in the following equation:

$$\begin{aligned}&\textbf{Relative simple index score}(\mathbf{v}2)\\&= \Big| \boldsymbol{Index\ score\_t_2}\Big(\sum(-\mathbf{1}{*}\boldsymbol{rank}\mathbf{CT}_{1\ldots12})\Big)\\&\quad - \boldsymbol{Index\ score\_t_1}\Big(\sum(-\mathbf{1}{*}\boldsymbol{rank}\mathbf{CT}_{1\ldots12})\Big)\Big|\end{aligned}$$

In this equation, t_1 refers to an earlier time point (e.g., 2006), and t_2 indicates the later time point (e.g., 2016). $CT_{1\ldots12}$ stand for the values of 12 indicators in a CT.

Mean-centred index of change

Admittedly, we acknowledge these two simple approaches discussed above are not appealing to academic reviewers in peer-reviewed publications because statistical analyses in academic research require greater complexity in estimation and hypothesis testing. Measures such as these are examined for reliability, validity of estimation, and potential risks for bias. As a result, to construct an index of neighbourhood change for academic audiences, it is important to apply mean-centred measures.

To calculate such an index, one follows many of the same steps used for constructing the aforementioned two simple indexes, but adds a few additional steps. Using the CT-level data, we first calculated z-scores for the absolute value of raw change between 2006 and 2016 for each measure to standardize the measurement of neighbourhood change. We then summed the z-scores (in absolute values) of all the 12 measures of change for each neighbourhood (CT or CSD) and divided the summed amount by 12. We call this a mean-centred index (v3). As with the two simple indexes, we used absolute index values to gauge the magnitude, rather than direction, of change. To be consistent with the two simple indexes for the general public, the mean-centred index values were then ranked into quintiles for each city.

The question is, however, do these additional steps result in a more effective index? Additionally, how consistent are the results produced by each index in estimating which neighbourhoods change the most? To this end, we compare the performance of the two simple indexes (v1 and v2) against that of the mean-centred index of change (v3) using descriptive statistics (quintiles, Cronbach's alpha, and correlations) and multivariate analysis (binary logistic regression). In the Appendix, we summarize the process of calculating v1, v2, and v3 in steps.

Results

We used the three indexes of neighbourhood change outlined above to measure the extent of overall changes in neighbourhoods in four Atlantic Canadian cities (Halifax, Moncton, St. John's, and Charlottetown) using 2006 and 2016 Canadian Census data. Table 1 shows the quintile of change for each neighbourhood. The first quintile (Q1) indicates the top 20% of change, while the fifth quintile (Q5) represents the bottom 20% of change according to the three indexes.

As Table 1 shows, in Moncton, two CTs (305000800 and 305001100) fall into the top quintile of change across all the three indexes. The relative simple index (v2) and the mean-centred index (v3) appear to produce similar neighbourhood rankings mainly for the top three quintiles (Q1, Q2, and Q3), whereas the simple index (v1) and v3 yield similar rankings for the lower quintiles (Q3, Q4, and Q5). Although Halifax is a larger city involving over 80 CTs, we find the top quintile CTs are fairly consistent across the three indexes; three CTs (205010000, 205010402, and 205012306) all fall into the top quintile of the three indexes. By contrast, v1 and v3 appear to be the most similar in neighbourhood ranking across Halifax. In St. John's, we find two CTs (1001300 and 1020201) fall into the top quintile of change across the three indexes, and again, v1 and v3 appear to be most similar in terms of ranking neighbourhoods. Finally, in Charlottetown, we find one CSD (1102033) is ranked in the top quintile across all three indexes. Interestingly, however, we find more consistency in ranking between v1 and v3 for Charlottetown than other cities.

Next, in Table 2, we report results for a series of Cronbach's alpha tests to explore consistency across the three indexes. We are particularly interested in examining to what extent the two simple indexes for the general audience (v1 and v2) rank CTs into the same quintiles as the index for the academic audience (v3). In our first set of results, we code all three indexes in quintiles (1 through 5), where quintile one represents the most changed neighbourhoods. First, we find the reliability coefficient across all three simple indexes is low (0.45). However, when we test v1 and v2 separately against v3, the alpha test between v1 and v3 produces an even lower coefficient (0.23). The alpha coefficient between v2 and v3 is much higher (0.60).

In the second half of Table 2, we repeat these analyses on a dichotomous version of the indexes (1 = top quintile; 0 = all others). We find across all three indexes, the alpha coefficient is slightly lower (0.45), and the consistency between v1 and v3 yields a higher alpha coefficient (0.37) than the previous set of results. We also find consistency between v2 and v3 is slightly lower than when we use quintiles. Overall, across all three indexes, the reliability coefficients, or their consistency across indexes, is low. However, there is much consistency between the relative simple (v2) and mean-centred (v3) indexes.

Table 3 displays two correlation matrices of the three index variables, coded as quintiles and dichotomies. We find v1 and v2 are weakly correlated, and v3 is weakly correlated with v1. However, there is a moderately positive correlation between v2 and v3. When the quintile ranking is coded into a binary variable (1 = the top quintile; 0 = other quintiles), the

Table 1
Comparison of CT and CSD quintiles of neighbourhood change, using the three study indexes

City	CTs (or CSDs)	Simple index (v1)	Relative simple index (v2)	Mean-centred index (v3)
Moncton	305000100	Q1	Q2	Q1
	305000800	Q1	Q1	Q1
	305001100	Q1	Q1	Q1
	305001300	Q1	Q2	Q1
	305010202	Q1	Q2	Q2
	305020000	Q1	Q1	Q1
	305000301	Q2	Q3	Q3
	305000600	Q2	Q4	Q3
	305000700	Q2	Q3	Q4
	305001401	Q2	Q5	Q5
	305010201	Q2	Q3	Q5
	305000303	Q3	Q4	Q4
	305000900	Q3	Q2	Q3
	305001001	Q3	Q3	Q2
	305001601	Q3	Q1	Q1
	305010100	Q3	Q4	Q5
	305011000	Q3	Q1	Q3
	305000200	Q4	Q3	Q2
	305000304	Q4	Q2	Q4
	305000500	Q4	Q4	Q4
	305001002	Q4	Q5	Q4
	305010000	Q4	Q5	Q3
	305000400	Q5	Q5	Q5
	305001200	Q5	Q4	Q5
	305001402	Q5	Q2	Q3
	305001500	Q5	Q5	Q2
	305001602	Q5	Q1	Q2
Halifax	205000300	Q1	Q4	Q1
	205000500	Q1	Q3	Q3
	205001700	Q1	Q2	Q5
	205002000	Q1	Q5	Q5
	205002300	Q1	Q3	Q2
	205002503	Q1	Q5	Q4
	205010000	Q1	Q1	Q1
	205010402	Q1	Q1	Q1
	205010501	Q1	Q3	Q3
	205010800	Q1	Q5	Q4
	205011200	Q1	Q3	Q3
	205011300	Q1	Q2	Q5
	205012000	Q1	Q1	Q2
	205012107	Q1	Q5	Q2
	205012304	Q1	Q5	Q1
	205012306	Q1	Q1	Q1
	205013101	Q1	Q2	Q3
	205013206	Q1	Q3	Q2
	205000402	Q2	Q3	Q4
	205000800	Q2	Q5	Q4
	205001100	Q2	Q4	Q4
	205001800	Q2	Q2	Q5
	205001900	Q2	Q1	Q4
	205002100	Q2	Q5	Q3

(Continued)

Table 1
(Continued)

City	CTs (or CSDs)	Simple index (v1)	Relative simple index (v2)	Mean-centred index (v3)
	205002400	Q2	Q3	Q5
	205002700	Q2	Q5	Q4
	205010200	Q2	Q4	Q3
	205012102	Q2	Q1	Q2
	205012108	Q2	Q4	Q3
	205012201	Q2	Q2	Q2
	205012203	Q2	Q4	Q5
	205012301	Q2	Q1	Q2
	205013102	Q2	Q3	Q4
	205013104	Q2	Q2	Q1
	205014201	Q2	Q2	Q4
	205000600	Q3	Q2	Q1
	205000700	Q3	Q1	Q1
	205000900	Q3	Q5	Q4
	205001000	Q3	Q4	Q3
	205001400	Q3	Q2	Q1
	205001500	Q3	Q4	Q5
	205001600	Q3	Q1	Q1
	205002200	Q3	Q1	Q1
	205010300	Q3	Q5	Q5
	205010401	Q3	Q5	Q3
	205011100	Q3	Q5	Q3
	205011400	Q3	Q1	Q3
	205012105	Q3	Q2	Q1
	205013105	Q3	Q1	Q3
	205013203	Q3	Q2	Q3
	205014000	Q3	Q2	Q3
	205015001	Q3	Q3	Q5
	205000100	Q4	Q4	Q2
	205001300	Q4	Q5	Q4
	205002501	Q4	Q2	Q2
	205002502	Q4	Q2	Q5
	205010100	Q4	Q1	Q2
	205010502	Q4	Q3	Q5
	205010601	Q4	Q3	Q1
	205010602	Q4	Q5	Q4
	205010900	Q4	Q1	Q2
	205011000	Q4	Q2	Q5
	205012106	Q4	Q4	Q4
	205012302	Q4	Q4	Q3
	205012305	Q4	Q1	Q4
	205014300	Q4	Q4	Q5
	205015002	Q4	Q3	Q5
	205015200	Q4	Q4	Q3
	205015400	Q4	Q3	Q4
	205000200	Q5	Q3	Q2
	205000401	Q5	Q4	Q3
	205001200	Q5	Q1	Q1
	205002601	Q5	Q3	Q5
	205002602	Q5	Q4	Q4
	205010700	Q5	Q2	Q1
	205012103	Q5	Q4	Q2

(Continued)

Table 1
(Continued)

City	CTs (or CSDs)	Simple index (v1)	Relative simple index (v2)	Mean-centred index (v3)
	205012202	Q5	Q3	Q5
	205013001	Q5	Q1	Q1
	205013002	Q5	Q5	Q4
	205013103	Q5	Q3	Q2
	205013204	Q5	Q4	Q1
	205013205	Q5	Q5	Q5
	205014100	Q5	Q1	Q1
	205014202	Q5	Q5	Q2
	205015100	Q5	Q3	Q2
	205015300	Q5	Q1	Q2
St. John's	1000200	Q1	Q3	Q2
	1000600	Q1	Q3	Q3
	1000700	Q1	Q2	Q5
	1000800	Q1	Q2	Q1
	1000900	Q1	Q5	Q1
	1001000	Q1	Q4	Q5
	1001300	Q1	Q1	Q1
	1001501	Q1	Q4	Q3
	1020001	Q1	Q5	Q2
	1020201	Q1	Q1	Q1
	1000400	Q2	Q4	Q5
	1000501	Q2	Q3	Q1
	1001100	Q2	Q4	Q4
	1001200	Q2	Q2	Q2
	1001502	Q2	Q1	Q1
	1001503	Q2	Q2	Q1
	1001700	Q2	Q2	Q4
	1011000	Q2	Q5	Q2
	1020202	Q2	Q1	Q2
	1000100	Q3	Q1	Q1
	1001400	Q3	Q3	Q4
	1001504	Q3	Q1	Q3
	1017002	Q3	Q1	Q3
	1017203	Q3	Q1	Q4
	1017205	Q3	Q1	Q3
	1020100	Q3	Q2	Q1
	1020205	Q3	Q4	Q3
	1030000	Q3	Q5	Q5
	1000301	Q4	Q5	Q4
	1000502	Q4	Q5	Q4
	1010001	Q4	Q5	Q4
	1010003	Q4	Q3	Q4
	1017001	Q4	Q3	Q3
	1017100	Q4	Q4	Q2
	1017206	Q4	Q2	Q5
	1030101	Q4	Q1	Q2
	1030200	Q4	Q3	Q3
	1000302	Q5	Q2	Q5
	1001600	Q5	Q4	Q5
	1010004	Q5	Q2	Q2
	1017202	Q5	Q3	Q5
	1017204	Q5	Q5	Q3
	1020002	Q5	Q4	Q5
	1020003	Q5	Q4	Q2
	1020204	Q5	Q5	Q4
	1030102	Q5	Q2	Q1
Charlottetown	1102014	Q1	Q3	Q2
	1102026	Q1	Q4	Q4
	1102028	Q1	Q3	Q4
	1102033	Q1	Q1	Q1
	1102049	Q2	Q4	Q5
	1102052	Q2	Q2	Q3
	1102054	Q2	Q4	Q4
	1102057	Q2	Q2	Q1
	1102030	Q3	Q2	Q3
	1102037	Q3	Q3	Q3
	1102040	Q3	Q5	Q4
	1102085	Q3	Q5	Q5
	1102050	Q4	Q3	Q1
	1102070	Q4	Q1	Q1
	1102075	Q4	Q4	Q3
	1102080	Q4	Q4	Q2
	1102048	Q5	Q2	Q2
	1102056	Q5	Q1	Q5
	1102065	Q5	Q1	Q2

Q1—top quintile (most change); Q2—second quintile; Q3—third quintile; Q4—fourth quintile; Q5—fifth quintile (least change).

Table 2
Chronbach's alphas for the three study indexes of neighbourhood change

Indicators	Chronbach's alphas
Variables coded in quintiles	
Simple index (v1), relative simple index (v2), and mean-centred index (v3)	0.45
Simple index (v1) and mean-centred index (v3)	0.23
Relative simple index (v2) and mean-centred index (v3)	0.60
Variables coded in dichotomy (1 = top quintile, 0 = others)	
Simple index (v1), relative simple index (v2), and mean-centred index (v3)	0.45
Simple index (v1) and mean-centred index (v3)	0.37
Relative simple index (v2) and mean-centred index (v3)	0.52

Table 3
Correlation tables for the three study indexes of neighbourhood change

	1	2	3	4	5	6
Variables coded in quintiles						
1 Simple index (v1)	1					
2 Relative simple index (v2)	0.088	1				
3 Mean-centred index (v3)	0.130	0.429	1			
Variables coded in dichotomy (1 = top quintile, 0 = others)						
4 Simple index (v1)				1		
5 Relative simple index (v2)				0.056	1	
6 Mean-centred index (v3)				0.231	0.354	1

analyses produce similar results, with the strongest correlation being reported between v2 and v3 (0.35).

In Tables 4 and 5, we examine the association between each of the three indexes coded as dichotomous variables (1 = the top quintile; 0 = other quintiles) and our 12 measures of neighbourhood change. We ran logistic regression models to identify which measures of change are associated with the most overall neighbourhood change across all three indexes. To this end, we regressed each index separately on two sets of independent variables. In the first set of analyses (Table 4), we included 12 neighbourhood measures in 2006 as independent variables to identify which of the 2006 characteristics contribute to the most neighbourhood change 10 years later, in 2016 (Table 4). In the second set of models (Table 5), we considered 12 composite measures of change (2006–2016) as independent variables. We aimed to compare these regression results across all three indexes.

First in Model 1 in Table 4, we examine which of the 12 composite measures of neighbourhood characteristics in 2006 contribute to the most overall change in 2016 for v1. The most noteworthy results can be found in both the economic and physical dimensions of change; the mean annual individual income and the percentage of low income households contribute to the most overall change, along with the percentage of households who are renters/tenants. An increase in the percentage of low income households in 2006 is associated with reduced odds of contributing to the most change in 2016. An increase in individual annual income is also associated with increased odds of the

Table 4
Binary logit models predicting being in the top quintile of overall neighbourhood change using the 2006 neighbourhood characteristics as the independent variables

	Model 1 Simple index (v1)		**Model 2 Relative simple index (v2)**		**Model 3 Mean-centred index (v3)**	
Variables (characteristics in 2006)	**OR**	***p***	**OR**	***p***	**OR**	***p***
Economic measures						
% lone parent families	1.06	0.254	1.02	0.656	0.94	0.232
% low income households	0.96	0.029	0.97	0.048	1.01	0.469
Average individual income (in $1,000)	1.18	0.024	0.94	0.392	1.11	0.087
Unemployment rate	1.03	0.733	1.01	0.905	1.05	0.520
Sociocultural measures						
% aged 65 and older	1.01	0.898	1.06	0.252	1.05	0.362
% immigrants	0.99	0.921	0.98	0.851	0.99	0.900
% visible minorities	0.91	0.233	0.96	0.596	0.95	0.456
% bachelor's or higher degree holders	1.00	0.959	1.04	0.332	0.97	0.400
Physical measures						
% apartment dwellings	0.95	0.067	1.04	0.138	1.01	0.829
% renter/tenant households	1.07	0.018	0.93	0.075	1.03	0.384
% one-person households	1.00	0.967	1.04	0.598	0.94	0.389
% dwellings requiring major repairs	0.98	0.651	0.94	0.176	1.09	0.026
Intercept	0.00	0.001	1.70	0.746	0.01	0.004
−2 log likelihood	157.29		171.87		172.63	

Table 5
Binary logit models predicting being in the top quintile of overall neighbourhood change using the 2006–2016 neighbourhood characteristics changes as the independent variables

Variables (Changes from 2006 to 2016)	**Model 1 Simple index (v1)**		**Model 2 Relative simple index (v2)**		**Model 3 Mean-centred index (v3)**	
	OR	***p***	**OR**	***p***	**OR**	***p***
Economic measures						
% lone parent families	0.99	0.911	0.96	0.368	1.01	0.873
% low income households	1.04	0.042	1.00	0.82	0.98	0.195
Average individual income (in $1,000)	1.13	0.006	1.04	0.292	1.04	0.319
Unemployment rate	1.20	0.035	1.06	0.459	1.04	0.629
Sociocultural measures						
% aged 65 and older	1.32	0.001	1.18	0.006	1.14	0.025
% immigrants	1.24	0.028	1.03	0.68	1.02	0.769
% visible minorities	1.02	0.689	1.02	0.534	1.04	0.132
% bachelor's or higher degree holders	1.18	0.007	0.96	0.435	0.96	0.410
Physical measures						
% apartment dwellings	0.99	0.887	1.04	0.461	1.06	0.278
% renter/tenant households	1.29	0.000	1.05	0.236	1.03	0.499
% one-person households	1.06	0.607	0.98	0.824	0.99	0.917
% dwellings requiring major repairs	0.97	0.692	1.13	0.028	1.00	0.967
Intercept	0.00	0.000	0.08	0.002	0.07	0.000
−2 log likelihood	125.29		168.75		173.26	

most neighbourhood change in 2016. Further, an increase in the percentage of households who are renters/tenants in 2006 is associated with increased odds of the most change in 2016. However, little evidence suggests the sociocultural measures in 2006 contribute to the most overall neighbourhood change in 2016.

In Model 2, we repeat these analyses using v2. Of the 12 composite measures, the measures contributing to the most neighbourhood change in 2016 are in the economic and physical dimensions, similar to Model 1. An increase in the percentage of low income households is associated with reduced odds of the most neighbourhood change in 2016. However, in contrast to Model 1, an increase in the percentage of households who are renters/tenants reduces the odds of the most neighbourhood change.

In Model 3, we regress v3 on the 12 neighbourhood measures in 2006. Similar to Models 1 and 2, the physical neighbourhood dimension appears to be driving the most change. However, in contrast to the other two models, an increase in the mean individual annual income and an increase in the percentage of dwellings requiring major repair are contributing to the most change. In particular, an increase in individual annual income and dwellings requiring major repair are associated with increased odds of the most neighbourhood change.

In Table 5, we regress each of the three indexes of change on 12 composite measures of change from 2006 to 2016. Logistic regression results for v1 in Model 1 show composite measures from each of the three dimensions of neighbourhood change are contributing to the most neighbourhood change, with a greater proportion of economic measures contributing to the most change. We find increases in the unemployment rate, mean individual annual income, and the percentage of low income households between 2006 and 2016 are associated with increased odds of the most neighbourhood change. Moreover, increases in the percentages of immigrants, university degree holders, and residents aged 65 and older between 2006 and 2016 (from the sociocultural dimension) are associated with increased odds of the most neighbourhood change between 2006 and 2016. Further, an increase in the percentage of households who are renters/tenants is associated with increased odds of the most neighbourhood change.

Model 2 shows less variability of relative change across the three dimensions (economic, sociocultural, and physical). Instead, we find increases in the percentages of residents aged 65 and older and dwellings requiring major repair between 2006 and 2016 are associated with increased odds of the most relative neighbourhood change.

Finally, the mean-centred index of change again shows less variability across the three dimensions (Model 3). Consistent with the other two indexes, an increase in the percentage of residents aged 65 and older from 2006 to 2016 is associated with increased odds of the most overall neighbourhood change.

Conclusion

In this paper, we discussed the steps and considerations needed to create a simple index of neighbourhood change. We also explored whether it could be calculated, with basic math skills using a spreadsheet with publicly available data, as effectively as an index that is mean-centred and meets the basic standards of academic peer-reviews. We did this because of the increasing prominence of indexes of neighbourhood change and the lack of understanding of how they work by the general public. One of the aims of the paper was to offer basic and practical advice on how to create such an index. We also aimed to help students and researchers understand how to think about indexes and translate their work for more general audiences.

We presented three methods of calculating neighbourhood change indexes, two simple and one slightly more sophisticated. Overall, we found the raw calculation that captures one-to-one changes of different variables (v1) is least consistent with the other indexes (v2 and v3). By contrast, we found the relative simple index (v2) has surprising consistency with the mean-centred approach. Although some general differences in results exist, our analysis showed the relative index is fairly consistent in identifying the neighbourhoods that experience the most change and the factors contributing to those changes compared to the mean-centred approach used in academic literature. As such, we conclude the relative simple index (v2) is a particularly promising tool for urban planners and NGOs, who may not have advanced statistical training, to measure changes in neighbourhoods using publicly available data.

The indexes help to identify the areas of the city experiencing the most and least change across dimensions. This allows community groups to identify where to target their attention. Neighbourhoods in cities often develop reputations or histories for gentrifying or needing attention which at times mask other neighbourhoods that are changing and are also deserving of attention. This being said, change on its own is not necessarily positive or negative. Rather, we contend simple indexes are useful tools for urban planners, academics, and community groups to identify where to focus more attention and deploy additional resources to investigate, such as follow-up interviews or surveys or more sophisticated analysis.

We suggest there is a power to a simple approach. It is a power that allows general users, community groups, and the broader public to use publicly available data and simple analytical techniques to assess neighbourhood change and contribute to the academic and policy discussion. In an era with increasing open data and the use of indexes and analytics in policymaking, it is important to increase the accessibility and transparency of methods used to assess neighbourhoods and changes in them. We hope this paper helps empower a broader set of urban planners, NGOs, community members, students, and researchers to use indexes.

Acknowledgements

This research was supported by the Social Sciences and Humanities Research Council of Canada as part of the Perceptions of Change Project (http://perceptionsofchange.ca). We thank the editor and two anonymous reviewers of *The Canadian Geographer* for their helpful comments.

References

Andersson, R., and L.M. Turner. 2014. Segregation, gentrification, and residualisation: From public housing to market-driven housing allocation in inner city Stockholm. *International Journal of Housing Policy* 14(1): 3–29.

Atkinson, R. 2000. Measuring gentrification and displacement in greater London. *Urban Studies* 37(1): 149–165.

Baxter, V. 2010. Prosperity, immigration, and neighborhood change in Silicon Valley: 1990–2000. *Sociological Spectrum* 30(3): 338–364.

Brown-Saracino, J. 2009. *A neighborhood that never changes: Gentrification, social preservation, and the search for authenticity*. Chicago, IL: University of Chicago Press.

—— 2017. Explicating divided approaches to gentrification and growing income inequality. *Annual Review of Sociology* 43: 515–539.

Centre of Urban Studies. 1964. *London: Aspects of change* (No. 3). London, UK: MacGibbon and Kee.

CHASS (Computing in the Humanities and Social Sciences). 2015. *CHASS Data Centre*. http://dc.chass.utoronto.ca/census/

Coulton, J. C., Z. M. Jennings, and T. Chan. 2013. How big is my neighborhood? Individual and contextual effects on perceptions of neighborhood scale. *American Journal of Community Psychology* 51(1–2): 140–150.

Eckerd, A. 2011. Cleaning up without clearing out? A spatial assessment of environmental gentrification. *Urban Affairs Review* 47(1): 31–59.

Frey, W. H., and R. Farley. 1996. Latino, Asian, and Black segregation in US metropolitan areas: Are multiethnic metros different. *Demography* 33(1): 35–50.

Galster, G. 2001. On the nature of neighbourhood. *Urban Studies* 38(12): 2111–2124.

Germain, A., and J. E. Gagnon. 1999. Is neighbourhood a black box? A reply to Galster, Metzger and Waite. *Canadian Journal of Urban Research* 18(2): 72–184.

Government of Canada. 2021. *Open data*. https://open.canada.ca/en/open-data

Halifax Partnership. 2019. *Halifax index 2019*. Halifax, NS: Halifax Partnership. https://halifaxpartnership.com/sites/default/uploads/pages/downloads/Halifax_Index_jun14-2019-Printable-Version.pdf

Hammel, J. D., and E. K. Wyly. 1996. A model for identifying gentrified areas with census data. *Urban Geography* 17(3): 248–268.

Hamnett, C. 1991. The blind men and the elephant: The explanation of gentrification. *Transactions of the Institute of British Geographers* 16(2): 173–189.

Hwang, J. 2020. Gentrification without segregation? Race, immigration, and renewal in a diversifying city. *City & Community* 19(3): 538–572.

Jackson, J. 2015. The consequences of gentrification for racial change in Washington, DC. *Housing Policy Debate* 25(2): 353–373.

Jones, C. E., and D. Ley. 2016. Transit-oriented development and gentrification along Metro Vancouver's low-income SkyTrain corridor. *The Canadian Geographer* 60(1): 9–22.

Jun, H. 2013. Determinants of neighborhood change: A multilevel analysis. *Urban Affairs Review* 49(3): 319–352.

Kaida, L., H. Ramos, D. Singh, and R. McLay. 2020. How to capture neighborhood change in small cities. *Canadian Studies in Population* 47: 95–205.

Kaida, L., H. Ramos, D. Singh, P. Pritchard, and R. Wijesingha. 2020. Can rust belt or three cities explain the sociospatial changes in Atlantic Canadian cities? *City & Community* 19(1): 191–216.

Kitchen, P., and A. Williams. 2009. Measuring neighborhood social change in Saskatoon, Canada: A geographic analysis. *Urban Geography* 30(3): 261–288.

Lee, A. B., and K. E. Campbell. 1997. Common ground? Urban neighborhoods as survey respondents see them. *Social Science Quarterly* 78(4): 922–936.

Lees, L., T. Slater, and E. Wyly. 2013. *Gentrification*. New York, NY: Routledge.

Ley, D. 1987. Styles of the times: Liberal and neo-conservative landscapes in inner Vancouver, 1968–1986. *Journal of Historical Geography* 13(1): 40–56.

—— 1994. Gentrification and the politics of the new middle class. *Environment and Planning D: Society and Space* 12(1): 53–74.

Ley, D., and C. Dobson. 2008. Are there limits to gentrification? The contexts of impeded gentrification in Vancouver. *Urban Studies* 45(12): 2471–2498.

Logan, J. R., and C. Zhang. 2010. Global neighborhoods: New pathways to diversity and separation. *American Journal of Sociology* 115(4): 1069–1109.

MacDonald, J. M., and R. J. Stokes. 2020. Gentrification, land use, and crime. *Annual Review of Criminology* 3: 121–138.

Meagher, S. 2010. *A neighbourhood vitality index: An approach to measuring neighbourhood well-being*. Toronto, ON: United Way of Toronto. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.599.6708%26rep=rep1%26type=pdf

Meegan, R., and A. Mitchell. 2001. It's not community round here, it's neighbourhood: Neighbourhood change and cohesion in urban regeneration policies. *Urban Studies* 38(12): 2167–2194.

Meligrana, J., and A. Skaburskis. 2005. Extent, location and profiles of continuing gentrification in Canadian metropolitan areas, 1981-2001. *Urban Studies* 42(9): 1569–1592.

Meltzer, R., and J. Schuetz. 2012. Bodegas or bagel shops? Neighborhood differences in retail and household services. *Economic Development Quarterly* 26(1): 73–94.

Mok, D. 2010. The spatiality and cost of language identity. *International Regional Science Review* 33(3): 264–301.

Neighbourhood Change Research Partnership. 2021. *Neighbourhood change & building inclusive communities from within*. http://neighbourhoodchange.ca/

Nevarez, L., and J. Simons. 2020. Small-city dualism in the metro hinterland: The racialized "Brooklynization" of New York's Hudson Valley. *City & Community* 19(1): 16–43.

Nicotera, N. 2007. Measuring neighborhood: A conundrum for human services researchers and practitioners. *American Journal of Community Psychology* 40(1–2): 26–51.

Prouse, V., H. Ramos, J. Grant, and M. Radice. 2014. How scale matters: The modifiable areal unit problem and interpreting income inequality in the Halifax regional municipality. *Canadian Journal of Urban Research* 23(s1): 61–82.

Rosenthal, S. S. 2008. Old homes, externalities, and poor neighborhoods: A model of urban decline and renewal. *Journal of Urban Economics* 63(3): 816–840.

Social Planning Council of Ottawa. 2019. *The index: About the neighbourhood equity index*. https://neighbourhoodequity.ca/index2/

Steinmetz-Wood, M., R. Wasfi, G. Parker, L. Bornstein, J. Caron, and Y. Kestens. Y. 2017. Is gentrification all bad? Positive association between gentrification and individual's perceived neighborhood collective efficacy in Montreal, Canada. *International Journal of Health Geographics* 16(1): 24.

Swaroop, S., and J. D. Morenoff. 2006. Building community: The neighborhood social organization. *Social Forces* 84(3): 1665–1695.

Van Criekingen, M., and J. M. Decroly. 2003. Revisiting the diversity of gentrification: Neighbourhood renewal processes in Brussels and Montreal. *Urban Studies* 40(12): 2451–2468.

Vigdor, J. L. 2010. Is urban decay bad? Is urban revitalization bad too? *Journal of Urban Economics* 68(3): 277–289.

Walks, R. A. 2001. The social ecology of the post-Fordist/global city? Economic restructuring and socio-spatial polarization in the Toronto urban region. *Urban Studies* 38(3): 407–447.

—— 2007. The boundaries of suburban discontent? Urban definitions and neighbourhood political effects. *The Canadian Geographer* 51(2): 160–185.

Walks, R. A., and R. Maaranen. 2008. Gentrification, social mix, and social polarization: Testing the linkages in large Canadian cities. *Urban Geography* 29(4): 293–326.

William, C. A., and P. S. Morrison. 2012. Socio-spatial mobility and residential sorting: Evidence from a large-scale survey. *Urban Studies* 49(15): 3253–3270.

Appendix: Steps to calculating simple indexes and the mean-centred index of neighbourhood change

Three dimensions of change and its indicators (Unit of analyses: Census Tract or Census Subdivision)

- **Economic dimension**

1. % of lone parent families
2. % of low income households
3. Average individual income
4. Unemployment rate

- **Sociocultural dimension**

1. % of the population aged 65 and older
2. % of the population who are immigrants
3. % of the population who are visible minorities
4. % of the population with a bachelor's degree or higher

- **Physical dimension**

1. % of apartment dwellings
2. % of renter/tenant households
3. % of one-person households
4. % of dwellings in need of major repairs

$$\textbf{Simple index score}(\mathbf{v}1) = \sum(-\mathbf{1}*\mathit{rank}|\mathbf{CT}_{t_2}\text{–}\mathbf{CT}_{t_1}|)$$

Step 1. Calculate the raw difference across 12 indicators between two time points (e.g., 2006 to 2016).
Step 2. The calculated differences are then changed to absolute values.
Step 3. Reverse rank absolute values across all CTs for each measure from the most to least changed, where 1 indicates the most change.
Step 4. The ranked scored for all 12 measures are then summed, producing an absolute raw change index score.
Step 5. CTs are then sorted into quintiles based on the index values.

Relative simple index score (v2) = | *Index score_t*$_2$ (Σ(-*1*rank* $CT_{1\ldots12}$)) - *Index score_t*$_1$ (Σ(-*1*rank* $CT_{1\ldots12}$))|

Step 1. Rank CTs by values for each measure, where the highest value of a measure is ranked as 1. This is done separately for each time point included in the analyses (e.g., 2006 and 2016).
Step 2. Sum the ranking for each year across the 12 measures, producing two indexes (one for each year).
Step 3. Subtract index 1 (time point 1) from index 2 (time point 2).
Step 4. The calculated differences are then changed to absolute values.
Step 5. Reverse rank the values, so the highest value is ranked 1 (indicating the most change).
Step 5. CT scores are then sorted into quintiles based on the index values.

Mean-centred index of change (v3)

Step 1. Calculate the raw differences across 12 indicators between two time points (e.g., 2006 and 2016).
Step 2. The calculated differences are then changed to absolute values.
Step 3. Calculate z-scores for the absolute value of raw differences for each of the 12 measures, this will standardize the measurement.
Step 4. Sum the calculated z-scores (in absolute values) for all the 12 measures across all CTs, then divide the sum by 12.
Step 5. The values (which are now mean-centred) are then ranked into quintiles.