Living Conditions Index (LCI): A Context-based Measure to Understand Children's Developmental Outcomes*

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Summary

The scope of this study ranges from the identification of key drivers of living conditions from a wide spectrum of context-based and/or ecological indicators to the development of a concrete composite measure of living conditions within the framework of a multivariate analysis. The LCI is a standardized aggregate score that summarizes five components and 18 indicators in a single number. Three different approaches, Principal Component Analysis (PCA), Range Equalization (RE), and Division by Mean (DM) are used to assess the impact of different methods of weighting and standardization procedures on the composite. Between the RE and DM methods, the RE method is preferred because it accounts for wider variations and strong correlations to the PCA composite. In general, the PCA method appears promising, particularly for cross-community comparisons as it is based on a weighting scheme. Extreme variability between quintiles that comprise the LCI indicates that the score represents a summary of economic, housing, and cultural diversities. The paper advocates for a future plan of research in the light of identified gaps in data, and more emphasis on disparities in economic conditions. A major implication of the study is that the composite provides a new tool in child development research for characterizing community-based living conditions and detecting disparities in the distribution of child developmental outcomes.

Introduction

As an integrative tool for monitoring developmental milestones, researchers and policy makers resort to deficiencies in resources and opportunities in people's lives. The Human Development Index (HDI), Sustainable Society Index (SSI), and Health System Achievement Index (HSAI) are typical examples of monitoring tools that assume very important roles in international public policy debates and analysis in the international scene. The rationale behind all of these composite indicator initiatives is that a community, region, or nation needs to know how it is performing in measures or factors of economic, social, environment, health/longevity, and human rights and freedoms. In this context, assembling empirical evidence on the impact of an index of living conditions on observable outcomes in health and well-being of children is of key importance.

The primary purpose of any child development research is to improve the quality of life of children, by providing them an opportunity to realize their life chances and rights. The improvement of living conditions of children and their families could be one of the most explicit ways of attaining or improving children's wellbeing. The present study aims at developing a Living Conditions Index (LCI) in order to address inter-community disparities in young children's developmental outcomes with LCI as one of the contributing factors.[1] The broad objectives are as follows:

- Identifying indicators reflecting living standards across small areas beyond that conveyed by conventional socio-economic measures;
- Consolidating the indicators into components;
- Examining the interdependency between the multi-dimensional components; and
- Constructing a composite index for capturing objective measures of overall well-being.

At the outset, the present paper provides a comprehensive discussion about the choices involved in the construction of the LCI. In particular, we discuss different approaches to standardization and weighting of variables. We conclude the paper by discussing the applications of the index in understanding the early child development outcomes.

Children's Developmental Outcomes and Societal Well-being: Possibilities of a Link

While many correlates of children's development have been identified, the importance of community living conditions in shaping children's development has been recognized, but has not been given due consideration in Canada. Evidence suggests that neighborhoods have an independent impact over and above individual demographic characteristics on children's health and wellbeing, especially in their physical activity (e.g., Saelens, Sallis, & Frank, 2003). In Australia, Hume, Salmon, & Ball (2005) examined children's perceptions of their environment in developing an objective measure of physical activity, using mapping and photographic techniques and accelerometers among 10-year old children. Churchman's (2003) research suggests that the road system, zoning practices, and the extent of safety are all influential in children's developmental experiences. High-walkability (with grid-street networks) and *lollipop*

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[1] The concept of a community is loosely defined for the present purpose, using a number of factors and/or geopolitical units, such as census dissemination areas (census-defined boundaries), archival neighborhood/community maps, and postal codes.

neighborhoods (with many cul-de-sacs) are factors that have been implicated in the physical wellbeing of children and adults. Frank, Schmid, Sallis, Chapman, & Saelens (2005), for example, reported that adults who live in high walkability neighborhoods (as measured by such indicators as residential density and intersection density) in Atlanta were 2.4 times more likely than those who live in low walkability neighborhoods to be involved in 30 minutes or more physical activity per day. In comparison to the research involving adults, however, very little is known about the role of neighborhood environments on children's development.

One of the popular approaches in understanding the influence of environment on children has been the ecological models and, in particular, Bronfenbrenner's bioecological theory (Bronfenbrenner & Morris, 1998). As a systems theory of child development, the basic premise of Bronfenbrenner's theory is that developmental transitions are products of a child's biological predisposition and the environment which the child is exposed to. Although some transitions are experienced by all children and youth, especially the ones that are due to hormonal changes, children, in general, experience most transitions in a unique way with unique outcomes; the contextual factors, whether they are subjectively or objectively measured, become forces that shape children's experiences. It thus becomes essential to examine the contextual factors to enhance our understanding of what promotes or hinders children's healthy development.

The objective of the proposed research is to identify a provincial set of indicators of community living conditions to form the basis for developing a composite measure. The inventory will be broadly reflective of the multiplicity of indicators and their definitions, domains, and categories because of the very fundamental nature of the concept as one that operates in a variety of disciplines, economics, philosophy, ethics, and so on. That is, the concept of quality (living condition) is multidimensional, leading us to the question – what constitute living conditions?

The Scope of Macro-Level Indicators of Well-being: A Literature Review

Macro-indicators provide a wealth of knowledge for analyzing social and economic trends. They include concepts such as quality of life, well-being, economic competitiveness, and social cohesion measurements. They all play an important role in socioeconomic policy. However, the methodologies and indicators of many of these concepts differ greatly depending on their scope and focus. An overview of the various applications of macro-level frameworks, along with an examination of their respective methodologies, is the purpose of this section. Generally speaking, macro-indicators can be applied in a multitude of settings and can be modified to meet the needs of researchers in a flexible manner.

A variety of tools have been developed to measure quality of life. The Good Society Framework (GSF) developed by Jordan (2010) provided a comprehensive means of determining quality of life using a range of indexes. The model of well-being in the GSF uses various indexes to compile nine dimensions: relationships; economy; environment and infrastructure; health; peace and security; culture and leisure; spirituality, religion and philosophy; education; and governance. These dimensions are not weighted, and, as such, the GSF can be used as a starting point for analyzing each dimension in terms of societal well-being. The 26-item WHOQOL-BREF instrument has fewer domains than the GSF, and includes physical health, psychological health, social relationships and environment (World Health Organization, 2004). Both can be used for cross-cultural comparisons of quality of life.

Other tools have focused on quality of life measurement in specific regions. Cvrlje and Ćorić (2010) defined both quality of life and standard of living using subjective and objective, like the Human Development Index

(HDI), with an emphasis on Croatia after the recent economic crisis. The authors argued that a standard of living measurement is dependent on a macro perspective, while quality of life measurement necessitates a micro perspective (Cvrlje & Ćorić, 2010). In addition, the Social and Cultural Planning Office (SCP) of the Dutch government used the Living Conditions Index (LCI) to measure facets of individual living conditions. Boelhouwer's (2002) paper discussed the LCI and its relevance to policy makers. The LCI was composed of indicators from eight clusters: housing, health, purchasing power, leisure activities, mobility, social participation, sport activity, and holiday. To describe the backgrounds of living conditions, education, income and paid employment are used. Living conditions are measured on an individual level, allowing analysis on a national level as well as analysis of different societal groups. By linking a variety of indexes, the author noted that greater insight into both structural and individual-level concentrations can be gained (Boelhouwer, 2002). Furthermore, Kolenikov (1998) proposed a regression model which quantifies quality of life in terms of a training sample in a national context in Russia. This methodology demonstrated adequate statistical significance and, therefore, was found to be effective as a practical measurement of quality of life. Lisov and Shaposhnikov (1989) measured the well-being of families through material indicators in order to create a typology of family groups in rural settings. The methods used and findings reached can guide the formulation of social policy aimed at improving the socioeconomic position of impoverished families according to their social status and demographic composition.

Quality of life measurements, however, are not without limits. Michalos (2011) identified the shortcomings of the French Commission on the Measurement of Economic Performance and Social Progress, including the inability of the Commission to use the GDP to factor in non-commoditized goods and services as well as its failure to quantify the level of services such as healthcare and their impact on society. Also noted was the Commission's lack of consideration of the negative results of certain economic activities, such as pollution. The author argued that, contrary to the Commission's position, linking sustainability with quality of life measures is necessary due to the desire for a quality of life that is sustainable (Michalos, 2011). Suggestions were made for improving a composite index to represent the multiple dimensions of such a quality of life.

Two studies examined poverty in particular. One study by Reinstadler & Ray (2010) confirmed previous findings that the analysis of the at-risk-of-poverty determinants can be enhanced by examining factors at a macro level. This study employed longitudinal data to obtain more accurate estimated parameters than previous studies, and assessed if the regional GDP and regional unemployment rate had an effect on the at-risk-of-poverty status in Europe. The other study focusing on poverty examined the Multidimensional Poverty Assessment Tool (MPAT), an instrument that, according to Cohen (2009), can be utilized as a structure to guide rural poverty reduction in the developing world. Subcomponent weightings and item valuation can be customized to best reflect major foci in a specific region, thus creating a context-specific MPAT, though the standardized form of the tool should be used when comparing projects. Each of these studies can be used to aid in policy discussion, while Cohen's (2009) can provide guidance for secondary data analysis utilizing survey data.

Health is also measured using macro-level frameworks. Fallowfield (2009) defined quality of life in relation to the health of an individual and discussed the importance of using patient-reported outcome assessments when appraising the benefits and dangers of treatments tested in clinical trials. Generic instruments, such as the Short Form 36 (SF-36) and Functional Assessment of Chronic Illness Therapy (FACIT), were discussed, and their use in non-clinical trial settings was proposed. A brief guide to selecting an instrument was also featured. The Philips Center for Health and Well-being (2010a) also provided an illuminating

quantitative study regarding how people in different countries perceive health and well-being. This study can be useful when making cross-cultural comparisons.

Environmental indexes were also used to measure environmental conditions and sustainability. Patterson & Jollands (2004) had analyzed headline indicators for tracking progress towards sustainable development goals in New Zealand. Their research indicated that headline indicators, sustainability and selection criteria must be defined to successfully select suitable headline indicators (Patterson & Jollands, 2004). Two potentially useful headline indicators, the Ecological Footprint and the Genuine Progress Indicator, were identified, though others, such as the Environmental Sustainability Index (ESI), were also reviewed. The study recommended continued exploration into creating a composite index for sustainable growth in New Zealand that measures the economic, social and environmental aspects of development.

Leschke, Watt & Finn (2008) aimed to comprehensively evaluate the nature of job quality in Europe with the European Job Quality Index (EJQI). The EJQI used 17 indicators with six sub-indices: wages; non-standard forms of payment; working time and work-life balance; working conditions and job security; skills and career development; and collective interest representation. The authors noted that an annual quantitative index of European job quality would allow for the tracking of shifts and a comparison between countries over time (Leschke et al., 2008).

A wide range of literature is available regarding economic competitiveness indexes, especially through the International Institute for Management Development (IMD). The IMD competitiveness report analyzed and ranked regional and national economic competitiveness based on economic performance, government efficiency, business efficiency and infrastructure (IMD World Competitiveness Center, 2010). Rosselet-McCauley (2011) offered an overview of the World Competitiveness Yearbook along with its possible applications. The methodology was discussed in detail, along with the calculations used to determine the standard deviation, rankings, trends, growth rates, and deflated values. In addition, Garelli (2011) reviewed the development of the concept of competitiveness over time and stressed the interdependent relationship between enterprises and nations necessary for competitiveness to exist.

Still, other economic competitiveness indicators have been formed independent of the IMD. The Australian government has assembled indexes that measure the economic competitiveness of cities in an international context (Major Cities Unit, 2010). The featured indexes vary from wide-ranging ones that measure general competitiveness to indexes that focus on key areas such as global connectivity and quality of life. This comprehensive assemblage of measurement tools provides an ample overview of economic and social measurement.

Indicators of social cohesion have recently been analyzed by Dickes, Valentova & Borsenberger (2009), who built on previous research regarding social cohesion indicators. The indicators were based on micro-data collected from one country, Luxembourg, from the 1999 European Values Study. The European Values Study consisted of both subjective and objective items that measure attitudes of and behavior concerning social relations, participation, and trust on many social levels as well as social domains. Multidimensional scaling and confirmatory factor analysis were used to achieve an empirical analysis and construction of social cohesion indicators.

Macro-level indexes are also used to analyze child development, child welfare and diversity in education. In terms of child development, a study by Fernald, Kariger, Engle & Raikes (2009) focused on low-income countries. Issues affecting early child development and its methods of measurement were reviewed, and an

analysis of different tests used with children less than five years of age, such as the Early Development Inventory (EDI) was included. The domains suggested for measurement consisted of cognitive skills, executive function, language skills, motor skills and socio-emotional development. Additionally, recommendations were included to aid in the planning of effective assessment with attention given to specific stages of early childhood. Another article relating to child development by Guhn & Goelman (2011) created a theoretical framework for guiding validation research within a population-level approach to child development research and for the EDI. Bronfenbrenner's bioecological theory served as the basis for this framework, although validity theory as well as social and health sciences were also major components. Guhn & Goelman's (2011) focus was on construct validity and test validation. The paper attempted to merge conceptual, theoretical, methodological and psychometric considerations while offering specific design, methodology and validation recommendations for a population-level approach to studying children's development and well-being.

One particular study provided a framework to track outcomes for children who were receiving child welfare services. The National Child Welfare Outcomes Indicator Matrix (NOM), developed by Trocmé, MacLaurin, Fallon, Shlonsky, Mulcahy & Esposito (2009), was composed of ten key indicators and four nested domains: child safety, child well-being, permanence, and family and community support. The Matrix employed standardized observational and self-report instruments that can track trends and assess the effectiveness of programs and policies.

The level of diversity in education was also measured using macro-indicators in terms of classroom activities, materials and displays in preschool classrooms. A study by Perlman, Kankesan & Zhang (2008) examined the impact of structural quality characteristics, such as staff training and education, on the diversity-positive classroom. Higher scores on a diversity instruction and materials index were predicted by the use of a variety of teaching formats, higher salaries, greater supervision, and having greater proportions of children who received a child care subsidy, as indicated by hierarchical linear model analyses (Perlman et al., 2008).

One study offered a framework to measure a field of study quite dissimilar than the ones previously discussed. However, considering its discussion of macro-level variables, it can be especially useful to researchers. De Bosscher, De Knop, van Bottenburg, & Shibli (2006) discussed the factors that can lead to international sporting success for nations in an international context. Their findings indicated that more than half of these factors were macro-level variables beyond the influence of government, while the meso-level was comprised of determinants that can be influenced by government sports policy (De Bosscher et al., 2006). A conceptual framework was presented that can be used for comparing professional sports policies on an international level.

Another important consideration for researchers is the theoretical assessment tools that have been utilized to measure macro-level data. According to Sirgy (2010), these concepts, when used in quality of life indicator projects, consisted of socio-economic development, personal utility, just society, human development, sustainability and functioning. One theoretical framework of note is the Sense of Community Index (SCI) (Chavis, Lee & Acosta, 2008). The SCI, a widely-used quantitative measure of sense of community, has been found to be a strong predictor of behaviors. The formulation of the Sense of Community version 2 (SCI-2) addressed all of the attributes of a sense of community using a 24 item scale (some of which were not addressed in the original index). Ultimately, this instrument served as an improved version of its predecessor, and can be an effective means to analyze social cohesion (Chavis et al., 2008). Another assessment tool of note is the Pareto Analysis. Haughey's (2010) guide to the analysis provided a

review of the seven steps of the analysis and of the statistical technique, which needed a small amount of tasks to produce a considerable effect overall. These components allowed for the identification of a limited number of important causes.

Methodologically, despite the importance of investigating the unidimensionality of item response data for construct validity, Slocum-Gori & Zumbo (2010) noted that there is no universal method to determine the number of factors to retain when assessing the dimensionality of the data. This study examined how various factor analysis procedures performed, both individually and in combination, during the assessment of the unidimensionality of item response data using computer simulated design. Varied conditions, including sample size, magnitude of communality, distribution of item responses, proportion of communality on second factor, and the number of items with non-zero loading on the second factor were used. The findings revealed that no single decision-making method identified unidimensionality under all conditions (Slocum-Gori & Zumbo, 2010). The paper also provided researchers with a set of guidelines and a new statistical methodology.

It is important to review the analyses of various assessment tools when considering macro-indicator frameworks. Various studies provided critical evaluations of such frameworks and offered suggestions for improvement. These considerations can be beneficial for researchers when deciding upon and constructing indicators. In one such analysis, the Philips Center for Health and Well-being (2010b) summarized the findings of the first think tank meeting on Livable Cities, and clustered the main discussions around three themes: resilience, inclusion and authenticity. Resilience was examined in terms of environmental, socio-cultural, and economic dimensions. The theme of inclusion was comprised of diversity, social integration and public safety, and equal access to urban qualities. Authenticity was assessed in terms of contextualized innovation as well as a sense of place and sense of belonging. The meeting discussed the need to measure the livability of a city as well as the need for the identification of new appropriate indicators. It was also noted that none of the emerging indexes are currently successful at a global level due to lack of acceptability, endorsements, or contextual applicability (Philips Center for Health and Well-being, 2010b). The paper stressed the scanning and filtering of emerging indicators for their relevance to themes of resilience, inclusion and authenticity.

Another analysis by the Center for Communication and Civic Engagement (2007) provided a brief review of the HDI by deconstructing its three equally weighted components: health, education and wealth. The correlation between HDI and GDP rankings was called into question, citing the disparity of both rankings for the United States. Validity, reliability and parsimony were also concisely reviewed.

Finally, Sharpe (2004) analyzed the conceptual and practical frameworks for the construction of macro-indicators that provided an evaluation of economic, social and labor market conditions of well-being. Frameworks for macro-indicators were discussed, along with the issues commonly associated with them. Six frameworks, including European Union social indicators, the HDI, the Index of Economic Well-being (IEWB) and economic gender equality indicators were also described with their strengths and weaknesses noted. Additionally, 31 sets of indicators and composite indexes were examined in terms of social, socioeconomic and labor market areas. The author stressed that the effectiveness of frameworks for macro-indicators were dependent on the domains of interest, the purpose, the population and other factors (Sharpe, 2004).

It is important to note, however, that macro-level measurements are not without limitations. For instance, the original SCI used a 12-item scale, the reliability of which, as Chavis et al. (2008) pointed out, is

sufficient, but notably low. Variability was limited by the true-false response set of the SCI, and its use as a cross-cultural measure has been questioned (Chavis et al., 2008). In addition, Boelhouwer (2002) noted that while the LCI can identify trends in living conditions and can recognize disadvantaged groups, it is largely a superficial breakdown of living conditions and cannot identify the reasons that certain groups are deprived. In addition, not all indicators of the LCI can be uniformly addressed by government policy (Boelhouwer, 2002). Furthermore, De Bosscher et al. (2006) pointed out that the use of certain variables is sometimes intended for specific regions and political organizations, such as Western capitalist democracies, and may need adjustment for meaningful use in developing countries. Almost all authors included suggestions for modifications and variables that are important to be considered in future studies.

Macro-indicators can be applied in various settings and can be customized to meet the needs of researchers. Ample data can be provided by macro-indicators for examining socioeconomic patterns to which social and economic policy can respond. Various areas of study, including quality of life, environmental well-being, job quality, economic competitiveness, social cohesion, and child-related data can be measured. Depending on their scope and focus, the methodologies and indicators used in many of these instruments differ greatly. An overview is provided in this literature review of the various applications of macro-level frameworks along with the different methodologies involved. Though the research discussed develops both the understanding and the practice of these measurements, further exploration into macro-level indicators will enhance the manner with which they are used.

Identification of Indicators for the Construction of the LCI

In view of the difficulties in reaching a general consensus on indicators for well-being or a composite such as LCI, we are constrained to use straight-forward indicators reflecting their relevance to the concept that is being measured. For example, if standard of living is to be considered, the disparities in incomes become a relevant indicator. Second, the choice of indicators is guided by the correlations between indicators. The inter-correlations can point to the redundancy of indicators to a greater extent, although an acceptable level of strength or lack of it is difficult to establish. Finally, the choice was made on the availability of official data sources to extract the indicators of interest. The indicators we thought important to be included are classified into seven categories: (1) demography/family structure; (2) economy/economic diversity; (3) gender equality; (4) housing; (5) education; (6) ethnicity/cultural diversity; and (7) density/infrastructure (Appendix Table 1).

Rationale for the Selection of Indicators

The extent, to which the selected indicators can map the living conditions of areas in either a non- or a linear form, needs to be examined.[2] Areas of different population distributions have different abilities to pool resources and those with low proportions of children and/or elderly do not need the same income or other resources to assure the same level of well-being for their members. For instance, an area consisting of less than five percent of its population below 5 years of age does not need as many kindergarten schools or day care centers as an area with 10 percent of its children under the same age. In general, demographic factors, either directly or indirectly, contribute to the living conditions of areas.

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[2] The value of certain variables, but not all, can have equal importance at various levels of the variable; the relative impact of variables, such as deprivation, can increase as the level of deprivation becomes sharper (Anand & Sen, 1997). Based on this argument, some measures of living conditions can have a diminishing return, while others can have increasing returns (Salzman, 2003).

Gross Domestic Product (GDP) per capita has long been used as the main indicator for measuring and comparing standard of living across regions and countries. The underlying assumption is that marketplaces are the avenues to exercise individuals' needs and wants and the consumption of goods and services is directly related to one's capacity to purchase them. In recent decades, especially since the 1980s, social and health indicators have gained more importance as indicators of well-being than conventional economic measures, although economic, and in particular, income measures continue to be used as proxies for well-being. Economic factors, in general, reflect the extent of participation in the economy and society and how well members are able to get through their life, by attaining education, employment, etc. At a macro-level, higher levels of income may also contribute to lower inequality and gender differences in education, employment, and income. OECD countries with lower GDP per capita are reported to have higher relative poverty and child poverty, although not necessarily lower earning differentials between men and women (Giovannini & Hall, 2007). Economic factors exclude a range of non-market activities that influence the well-being of people, mainly because they are not always observable, and even when they are observable, they cannot be attached with monetary value. These include unpaid housework and self-employment without any help. Such activities limit the amount of time that can be devoted to leisure, and consequently limit well-being. Differences in paid work and self-employment with no help can lead to differences in the amount of leisure time that people can enjoy.[3]

Housing not only reflects economic situations, but other social factors that can affect population health. The indicators of housing used are household size, age of dwellings, type of housing, and payments on housing. These indicators can be closely related to an area's income levels, meaning that, on average, higher income areas are more likely to have single-family dwellings, larger houses, and good housing. However, increases in incomes cannot always translate into new housing, because multiple-dwellings, apartments, and condominiums can be the result of population influx. Conventional measures of economic conditions do not always take account of assets, such as ownership of homes, although these clearly influence not only what an individual can consume in good and bad times, but also a feeling of security. Overall, housing provides information about a number of aspects of living conditions, beyond that which is conveyed by social and economic factors.

A feeling of belongingness to a community and society, if enjoyed by all members of a society, regardless of their racial and/or ethnic background, contribute to better participation in the society, and to overall well-being. However, racial and ethnic tensions, either due to differences in socio-economic situations or due to a lack of understanding of the culture and language, can adversely affect the standard of living of members of a society. The purchasing power of individuals goes hand-in-hand with their ability to fully integrate or participate in market economies.

The three indicators, distance to nearest city, percent who walk or (motor)bike to work, and intersection/cul-de-sac density, may reflect different underlying concepts, and may influence leisure and travel time, travel expenditures, social interactions or even cause some of the dysfunctions (e.g., safety concerns) arising from urbanization, city life, and environmental degradation (e.g., pollution). For example, for those who walk or bike to work, the quantity of leisure time can be increased, and they may have more time for personal and/or family care. Those who live in and around major cities may have better resources available to

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[3] While it is possible that such differences can vary according to cultural and/or personal preferences, they can serve as proxies for leisure and well-being. For an assessment of the impact of leisure time and income inequality on well-being, see Beckerman (1978).

secure well-being (e.g., walk-in clinics and health clubs) that may translate into good living conditions, although there can be exceptions.

The indicator intersection density refers to the number of intersections in an area and it corresponds closely to block size; the greater the intersection density, the smaller the blocks. Neighborhoods with small block size typically have better walkability (Schlossberg, 2002). Higher intersection density also contributes to better connectivity as neighborhoods with higher intersection density tend to be grid-style neighborhoods and can have shorter block lengths. The grid-style street patterns could give more route choice for pedestrians and, therefore shorter walking distances, compared to curvilinear street patterns. However, there can be exceptions. For example, some intersections can lead to dead ends, bottlenecks, or inaccessible gated areas (e.g., industrial areas), making it not so easy to walk. It is not necessarily an accurate measure of walkability, but, because it is easy to compute and has a broad geographic coverage, researchers often use it as a ballpark estimate for understanding the effects of built environment on walking, driving, and transit use.

It may be pointed out that the selection of indicators is almost always guided by availability of data, especially in a secondary analysis of this kind. It is difficult to provide hard empirical evidence to justify the selection of indicators or determine the nature of their relationships to the concept being measured. In light of these, anecdotal evidence would prove to be useful in developing a framework in the construction of a composite index. The economic indicators have always been drivers of well-being in cross-country analyses. However, they may lose their significance as societies move beyond their capacity to meet the basic necessities of food, shelter, and clothing (Giovannini & Hall, 2007).

Of the 50 indicators considered, Theil's T statistic is a mathematically elegant, but underutilized tool measuring inequality, compared to range, inter-quartile range, the Gini coefficient, and many others. Brief descriptions of Theil's T statistic and ethnic diversity index are in order (see also, footnotes for Appendix Table 1).

The Theil's T Statistic

Theil's T statistic is a measure used to quantify inequality between groups in a population. In economics, the Theil's T Statistic is often used to provide a measure of income inequality between state and national earning averages. Numerically, Theil's T can be interpreted as negative or positive in magnitude, where positive values suggest the sample mean is greater than the population mean weighted by the appropriate sample size, and negative values suggest the sample mean is smaller than the population. This statistic can be used to compare different sub-groups (e.g., sex), as the inequalities of each respective category are rescaled onto a common metric. The statistic is calculated by the product of three ratios: the proportion of sample size within the population, the proportion of sample mean with population mean and the natural logarithm of the aforementioned proportion (Hale, 2004). T can be written as follows:

$$T = \left(\frac{p_i}{P}\right) * \left(\frac{y_i}{\mu}\right) * \ln\left(\frac{y_i}{\mu}\right)$$

Where p_i is the population of group I, p is the total population, y_i is the average income in group i, and μ is the average income across the entire population.

The Index of Ethnic Diversity

The index of ethnic diversity is used to quantify the diversity of ethnic origins within the population (Balakrishnan & Jarvis, 1976). The index can be computed as:

$$1 - \sum p_i^2$$

Where p is the proportion of each ethnic background compared to the population, and all ethnic background proportions are squared then summed.

The index has a minimum of 0 and a maximum of 1, where high values suggest higher diversity within the given area. In addition, the index also takes account of the number of ethnic backgrounds, where more equally diverse backgrounds would result in a higher index value compared to disproportionate sets of ethnic backgrounds. The index is commonly used to describe and compare diversity of categories in different areas, and provide a summary index that can be easily compared in contrast to direct proportions.

Data and Methods

The selection of indicators does not fully depend on their theoretical importance. We aimed at maximizing our spatial units while maintaining adequate proxies that could adequately reflect various dimensions for the composite. The spatial unit used in the study is the Dissemination Area (DA). This is one type of standard spatial unit outlined in the 2006 Canadian Census geographic classification and is considered to portray stable boundaries. The Census data covered 5,222 DAs in Alberta. One of the main reasons why the DA is used as the spatial unit of analysis is that it is the smallest standard geographic area for which all Census data are disseminated. They are relatively stable geographic unit composed of one or more adjacent dissemination blocks. DA's cover contiguous areas of the whole province with no substantial issues when identifying community boundaries based on postal codes.

All the indicators, with the exception of distance to nearest city and intersection, cul-de-sac and population density, were derived from the DA-level profile of 2006 Census data published by Statistics Canada. The intersection density variable was calculated using Geographic Information System (GIS) techniques by aggregating intersections within each neighborhood and dividing by the total area of each neighborhood. Also included was cul-de-sac density, based on the concentration of cul-de-sac areas. Conceptually, the two variables can be highly correlated, and the inclusion of both would be redundant, but warrant correlation analysis and further evaluation.

Component Indices and the Aggregate Index

The calculation of the composite index in this paper adopted the approach by Nardo, Saisana, Saltelli, Tarantola, Hoffman, & Giovannini (2005a), and follows these steps in the order in which they are outlined: consistency analysis; normalization and standardization; weighting; and aggregation. Three different techniques were used to calculate the index: Principal Components Analysis (PCA), Range Equalization (RE), and Division by Mean (DM).

Consistency Analysis

The Cronbach's Alpha and other measures, such as Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) and Bartlett's Test of Sphericity, are important prior to conducting factor analyses (Principal Component Analyses) to determine whether the results of the factor analyses are plausible. The Cronbach's Alpha was used to examine the extent to which the indicators are dependent of one another; a high value is an indication that the indicators pertaining to a concept capture the desired concept well. The Cronbach's Alpha for the data was set at Nunally's (1978) cut-off value of 0.7.

Both the KMO measure of sampling adequacy, based on the partial correlations among the indicators, and the Bartlett's Test of Sphericity, a warning sign of the identity of the correlation matrix, relate to factor analyses. According to Kaiser and Rice (1974), the MSA value should be greater than or equal to 0.5 to proceed with the factor analysis (see, Groh & Wich, 2009). The Bartlett's Test value should be below the 0.05 significance level.

Normalization and Standardization

Most indicator values do not fall in a normally distributed curve; some will be positively skewed where most of the areas record low values on an indicator (e.g., percent with science and/or engineering degrees) and some will have a negatively skewed distribution, where most values are at the high end (e.g., employment rate). Given that the relationship between indicators is assumed to be linear in factor analyses, non-normal indicators are transformed using various formulas based on the shape of the distribution. As part of the initial data cleaning process, and because factor analysis can be sensitive to outliers, these were either removed or substituted with lesser extreme values.

Standardization of variables is motivated by the fact that whereas some indicators (e.g., employment rate) correspond to increases in living conditions, others (e.g., divorce rate) correspond to decreases in living conditions. The Z-score transformation of indicators gives all indicators a normally distributed scale with mean equal to 0 and standard deviation equal to 1, and is a commonly used method before the aggregation of indicators. Another commonly used approach is rescaling, whereby the indicators are normalized to a common range. In computing HDI, UNDP has adopted the method of Range Equalization (RE) and also the Division by Mean (DM) method (UNDP, 2004). In this paper, both these approaches were used before the aggregation of the constituent parts of the LCI. The two methods are further discussed below.[4]

Principal Components Analysis (PCA): In the absence of individual level variables, constructing area-based indices built from weights derived from PCA has the potential to explain inequality between areas using comprehensive, readily available data. Further, PCA is computationally easy and also avoids many of the problems associated with the traditional methods, such as aggregation, standardization, and nonlinear relationships of variables affecting socioeconomic inequalities (refer Vyas & Kumaranayake, 2006, for an assessment of advantages and disadvantages of PCA and Saltelli, Nardo, Saisana, & Tarantola, 2004, for the pros and cons of composite indicator, in general).

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[4] A peculiarity of our data is that some indicators have very little variation across areas. Considering this, the rescaling approach seems more suited for our purpose so that the interpretations can be more meaningful and easier.

Range Equalization (RE) Method*:* The component index for a category, such as the economic factor, is obtained by first making all the economy-linked indicators scale-free. This is done by subtracting an indicator's minimum value from each observation and then dividing it by its range.[5]

$$\frac{Score - Minimum}{Maximum - Minimum}$$

Without scaling, a composite index can be biased toward an indicator with the highest range. For example, if *youth literacy rate* has its range double the size of *percent with post secondary education,* and if they are used as un-scaled variables in the composite, then youth literacy rate will cause the aggregate to have undue weight.

Division by Mean (DM) Method: The scale-free value of each indicator in a component index is obtained by dividing the indicator by its own mean. The method permits the coefficients of variation of different indicators within the component to remain different even after they are made scale-free.[6]

Weighting

For this paper, we used both equal weighting and weighting (determined by factor analyses) approaches before aggregation. Of the two approaches, equal weighting appears to be more common and also straightforward. In the weighting approach based on Principal Component Analysis (PCA), each component is given a weight according to its contribution to the total variance in the data (see, Nardo, Saisana, Saltelli, & Tarantola, 2005b). The calculation of the weights for each of the components is done by squaring the component loadings (the proportion of the variance of the indicator explained by the factors) and dividing it by the variance explained by the model.

Aggregation

Linear aggregation was used in this paper. Whereas linear aggregation is preferred when all the indicators have a uniform measurement scale, geometric aggregation is preferred when non-comparable and strictly positive indicators are measured in different scales (Ebert & Welsch, 2004). However, geometric aggregation, according to Nardo et al. (2005a), rewards areas and indicators with higher scores.

In light of the limited scope of this paper and also of the difficulties involved in putting together hard empirical evidence on the relative importance of one method over another, we have done a comparison of the techniques of standardization and weighting in arriving at a composite index. Composites, based on different approaches and methods, were then analyzed for their relationships to one another.

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[5] Instead of a division by an indicator range, fixed range, computed on the basis of pre-determined 'goalposts' with set upper- and lower limits has also been in use in the computation of composites (e.g., HDI). Fixing the goalposts for indicators can be tricky because not all indicators can be assumed to reach the upper value in the same fashion across time and space.

[6] The Coefficient of Variation (CV) is obtained by dividing the standard deviation of a variable by its mean. Graphically, it describes the peakedness of a unimodal distribution; the peak will be high and the CV will be small when the data points are bunched around the mean, and *vice versa.* A more equitable distribution has a smaller CV.

Results

PCA Method

The results of PCA using varimax rotation are presented in Table 1. Of 50 indicators, only 18 had loadings above 0.3 in absolute value and had no-cross loadings. None of the density variables loaded to any of the factors. Five components accounted for 64.20% of the variance in the data. This must be considered as an indication of the importance of chosen indicators in measuring the underlying concept and also the validation of PCA to extract components. For the first component, female after-tax income disparity, male after-tax income disparity, female employment income disparity, and male employment income disparity showed strong loadings, all above 0.8. What if the provincial picture did not reflect the exact employment income or after-tax income of males and females in every area? The difference in average after-tax and employment incomes for both males and females causes the inequality to widen. The first component accounted for 22.25% of the total variation. This component is a reasonable representation of economic diversity.

For the second component, one-family households, average household size, divorce rate, families with five or more members, and percent walk/bike/motor bike to work showed strong positive loadings. Although intersection density and cul-de-sac density turned out to be unimportant, the component highlights the importance of some of the positive features of grids and/or residential neighborhood designs that encourage active modes of transportation (walking, riding a bike, or riding a motor bike). The component accounted for 15.26% of the variance. We may interpret this component as representing housing/family structure. The third component accounted for 10.77% of the variance and explained the variations in illiteracy rate, post-secondary education, and Aboriginal population. The component represents the education dimension. The fourth component accounted for 8.04% of the variance and explained the variations in minority group membership. The fifth component is representative of the dependent population, children and seniors. The component accounted for 7.89% of the total variance.

Analysis of Index Consistency

In Table 2 are presented the Cronbach's Alphas for the five components and the two measures related to PCA. For the dependent population, the Cronbach's Alpha was below the cut-off value of 0.7, suggesting indicators with low indicator-total correlations. However, the mean-inter-indicator correlation was found to be 0.28, with values ranging from 0.148 to 0.414.[7] This suggests somewhat moderate relationships among the three indicators making up the component.

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[7] Cronbach's Alphas are dependent on the number of indicators in a dimension. When the indicators are fewer than 10, which is, of course, the case with all our components, it is recommended to calculate the mean inter-indicator correlation for the indicators. Optimal mean inter-indicator correlation values range from 0.2 to 0.4 (Briggs & Check, 1986).

Table 1 Results of Principal Components Analysis (PCA)

Variable	Loadings	Extraction Sums of Squared Loadings		
		Total	% of Variance	Cumulative %
Component 1				
Female after-tax Theil's T +	0.882			
Female employment Theil's T +	0.876			
Male after tax Theil's T +	0.880			
Male employment Theil's T +	0.871			
		4.005	22.247	22.247
Component 2				
Household size +	0.859			
Percent one family households +	0.880			
Percent divorced/separated out of married ++	0.804			
Percent family five plus persons +++	0.626			
Percent walk/bike/motorbike to work ++	0.523			
		2.746	15.257	37.504
Component 3				
Percent 15-64 illiteracy +	0.818			
Percent 25-64 post-secondary education ++++	0.714			
Percent aboriginal population –	0.651			
		1.939	10.770	48.274
Component 4				
Percent visible minority ++	0.840			
Percent third generation +	0.769			
Percent immigrated before age 14 –	0.677			
		1.447	8.038	56.312
Component 5				
Children under 5 out of 15 plus without income –	0.771			
Percent children under 14 home of all children !	0.656			
Percent seniors cared by 15 plus++	0.577			
		1,420	7.888	64.199

+ No transformation; ++ Reversed and log transformed (Log $_{10}$): +++ Transformed (sqrt): ++++ Reversed; - Transformed (Log 10); !Reversed, reflected, and transformed (sqrt)

Table 2: Consistency Analysis

Components	Cronbach's Alpha	MSA Value	Barlett's Test
Economic diversity	0.913	0.682	0.000
Housing	0.836	0.768	0.000
Education	0.771	0.556	0.000
Minority population	0.733	0.630	0.000
Dependent population	0.539	0.568	0.000

The Kaiser-Meyer-Olkin (KMO), a Measure of Sampling Adequacy (MSA) was used to detect multicollinearity in the data so that the appropriateness of carrying out a factor analysis can be detected. More specifically, MSA predicts if data are likely to factor well, based on correlations and partial correlations. For the overall model, the MSA was found to be 0.742, signaling that a factor analysis of the variables is appropriate (not shown on the Table). Another test of the strength of the relationship among variables was done using the Barlett's Test of Sphericity. The results showed a significance level of 0.00, a

value small enough to reject the null hypothesis that the indicators in the population correlation matrix are uncorrelated (χ^2 = 14356.32; df=190, sig=.000).

Index by PCA Method

Component-specific indices were computed, applying weights for the indicators and averaging them across the indicators (within the component) for each DA. The weights were computed by squaring the loadings and dividing the product by the variance explained by the component. An aggregate index was computed using the same methodologies.

The index scores presented in Table 3 measure the relative position of the DAs pertaining to living conditions. For index values, the higher the value, the poorer the living conditions. The scores exhibited wide inter-DA variation, as evident from the p-value of Levene's test; the p value should be less than 0.05 to reject the null that population variances are equal. The five groups ranged in mean scores from 34.74 to 67.89. DAs in the second quintile were more varied from those in the first quintile, compared to other quintiles.

Table 3: Mean Standardized LCI Scores by Quintile, PCA Method

Quintile	Mean	SD	95% CI
1	34.738	6.801	(34.325, 35.141)
2	46.516	2.186	(46.384, 46.649)
3	52.181	1.141	(52.112, 52.251)
4	57.575	1.761	(57.468, 57.251)
5	67.887	6.723	(67.479, 68.296)
Total	51.780	11.932	(51.456, 52.103)
Levene's statistic: 529.765; df1=4, df2=5217; sig=0.000			

Index by RE Method

In the RE method, the indicators in each component were divided by their respective range by first making each indicator scale-free by subtracting its minimum value from each observation. The indicators within each component were then aggregated and divided by the total number of indicators to obtain the score for the component index. The results are non-comparable to those obtained by PCA because an equal weighting scheme applies here. Interestingly, however, the gap between the fourth and fifth quintiles was found to be wider than any other adjoining quintiles (Table 4), suggesting that areas depicting higher scores on overall living conditions (i.e., poor living conditions) are more varied in absolute terms. Here too, inter-DA disparity appears significant, as evidenced by the p-value of the Levene's test.

Table 4: Mean standardized LCI Scores by Quintile, RE Method

Quintile	Mean	SD	95% CI
1	20.309	3.987	(20.067, 20.551)
2	27.468	1.295	(27.390, 27.547)
3	31.425	1.070	(31.360, 31.490)
4	35.921	1.650	(35.821, 36.021)
5	48.910	10.759	(48.256, 49.563)
Total	32.806	10.887	(32.511, 33.101)
Levene's statistic: 669.047; df1=4, df2=5217; sig=0.000			

Index by DM Method

In applying the DM method, the indicators in each component were divided by their respective means. Component-specific indices were obtained by aggregating the indicators and averaging them. The method yielded the same overall mean as in RE method (Table 5). Despite the overall mean being similar, the gaps in the values of the indices between quintiles were quite different; the gap between the third and fourth quintiles was as low as two units, whereas the gap between the fourth and fifth quintiles was eight units. It is important to note that the DM method also had significant inter-DA disparity.

Table 5: Mean Standardized LCI Scores by Quintile, DM Method

Quintile	Mean	SD	95% CI
1	25.118	6.755	(24.708, 25.528)
2	29.603	6.466	(29.210, 29.995)
3	32.398	7.223	(31.960, 32.837)
4	34.870	8.435	(34.358, 35.382)
5	42.043	14.938	(41.136, 42.950)
Total	32.806	10.887	(32.511, 33.101)
Levene's statistic: 219.399; df1=4, df2=5217; sig=0.000			

The PCA method, wherein each component is assigned a weight according to its contribution to the total variance in the data, gives the aggregate index a higher value. A major difference between the RE and MD approaches is that although we were able to eliminate scale-bias, disparity was more pronounced in RE, compared to DM. This disparity was evident in absolute as well as relative terms, when quintiles were considered.

It is not the purpose of this exercise to make a statement that a particular method is superior to another: the suitability of methods, in general, depends very much upon the objectives, the size of the geo-spatial unit, and also on the socioeconomic and cultural realities of the geo-spatial unit under consideration. However, what is clear from this exercise is that the choice of a method alters the values of component-specific indices, and thereby the aggregate index. According to the correlation analyses (not reported here), the PCA index was more strongly correlated to the RE index (r=0.692, p=0.01) than the DM index (r=0.047, p=0.01). Not surprisingly, the RE and DM indices were also strongly correlated (r=0.499, p=0.01).

Discussion and Conclusion

Much like the concept of satisfaction or quality of life, the concept of living conditions is complex and multifaceted and requires good data and thoughtful theoretical and methodological strategies. No single dimension stands as a reliable proxy for living conditions. Acknowledging this limitation, this study provides an assessment of the state of living conditions in an economically advanced province in Canada by bringing together the best of currently available macro-level indicators. Specifically, an attempt is made to measure and compare living conditions under five different components or dimensions by combining the components on the basis of PCA, RE, and DM methods of indexing. In all, this study looked at 50 indicators reflecting eight dimensions, and, through a process of elimination, arrived at five dimensions of 18 indicators. Grouping 18 indicators into five sub-indices and then a composite index enabled us to compare between small areas. The same procedures can provide insights into disparities in living conditions between larger geo-spatial units, such as Census Metropolitan Areas (CMAs), Census

Agglomerations (CAs), or regions within the province, in an objective way. More than just an equitable distribution of income for both sexes, but also social benefits (to groups with low levels of education, poor housing, etc.) may contribute to gains in overall living conditions.

A number of methods exist for operationalizing income inequality, and they offer researchers the means to quantitatively assess inequalities in different areas of the income spectrum. One of the central points of contention in this paper was how one such measure, the Theil's entropy measure contributes to a difference in meaning to a composite measure of living conditions. Acknowledging that income distributions cannot be adequately summarized in a single number in an absolute sense, four Theil's entropy measures measuring after-tax income and employment income for males and females were introduced. In other words, economic inequality was measured in a relative sense, i.e., how far an area falls behind or above the provincial average.[8] Thus, the choice of the income inequality component represents a significant advancement over previous works of this kind.

LCI scores calculated from three different methods point to a high level of differentiation along the continuum tapped by five components, even in a comparatively rich province with supposedly similar levels of governmental spending and policies in such areas as health and education. There is a pronounced pattern toward wider gaps within the lowest and also within the highest, in an absolute sense, compared to others in the middle quintiles. Overall, though it may be argued that in most areas of the province, economic inequalities are a reasonable proxy for disparities in living conditions, as evidenced by the contribution by this component towards overall explained variance.

Drawing upon the sociological, psychological, and health literature on child development, this research aims to provide researchers with additional tools with which to understand how macro-level factors influence some important dimensions of children's lives. What is to be gained by measuring or comparing living conditions in communities? An obvious answer lies in the maxim that to monitor or to improve any aspect of health or well-being, it first needs to be measured. Growing up in an environment with adequate standard of living and equitable access to services and opportunities is important for children's wellbeing. Given the potential value of children's well-being as an investment in the future of a society (UNICEF, 2007), it is quite obvious that measuring living standards helps set directions for policies and efforts. Measurement encourages, among other things, attention to gaps in data availability, consensuses or debates on what actually constitute living conditions; sound and reliable methodologies; and public understanding of living conditions.

When significant variations exist in terms of community living conditions, the implications of such variations may be tested for differences in child developmental outcomes. While a comprehensive multivariate analysis of the determinants of various child developmental domains is beyond the scope of this paper, future work will concentrate on an examination of the determinants of developmental domains by examining their relationships to socioeconomic status and living conditions at a community-level. A more comprehensive model seems desirable if we were to compare our living conditions index to other social issues already being considered, such as socioeconomic status and developmental trajectories of children.

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[8] Some may argue that many of those who fall below or above the average may have had incomes above or below the average at some point in the past and, therefore, relative measure of income does not reflect reality. However, in capitalist economies, the cutting edge of poverty is the perceived gap that exists between the poor and the rich. As Richard Wilkinson & Kate Pikett (2009) argued, inequality "gets under the skin" and makes everyone worse off, not just the poor (see also, The Economist, 2011).

Measures of early child development as the core aspects of a model, surrounded by LCI, socioeconomic status and other related aspects (e.g., resources and programs) will make the interrelationships between the concepts more visible, while marking the beginning of a new conceptual model of child development.

Acknowledgments

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Appendix Table 1: Description of 50 Selected Iindicators from DAs in Alberta, 2006

Variable	Description
Demography/Family Structure	
1.Percent population 65 plus years@	Population age 65 plus in the total population[((V17…V21 + V36…V40)/V2) *100]
2.Percent children under 14 home of all children q	Children under14 years at home of all children home [((V79+V80)/V78)*100]
3.Sex ratio, 0-4 years old $	Male children 0 to 4 to female children 0 to 4 [(V4/V23)*100]
4.Sex ratio, 5-9 years old $	Male children 5 to 9 to female children 5 to 9 [(V5/V24)*100]
5.Percent family five plus persons@	Census families with 5 or more persons [(V54/V50)*100]
6.Divorce/Separated out of married $	Divorced/separated 15 plus out of legally married [((V44+V45)/V43)*100]
7.Divorce/Separated out of population 15 plus $	Divorced/separated 15 plus out of all 15 plus population[((V44+V45)/V41)*100]
8.Percent seniors cared by 15 plus $	Population 15 plus providing unpaid care to seniors [(population 65 plus/V1190)*100]
Economy/Economic Diversity	
9.Percent employed population &	Population 15 plus employed of population 15 plus [(V577/V1)*100]
10.Percent employed labour force &	Population 15 plus employed of labour force 15 plus [(V577/V575)*100]
11.Economic dependency ratio $	Population under 15 or over 65 plus of all 15 to 64 [(V4…V6+V17…V21+V23…V25+V36…V40)/(V7…V16+V26…V35)*100]
12.Income dispersion ratio &	Population 15 plus with income above $50,000 to below $20,000 [(V1581+V1582)/(V1567…V1575)]
13.Children under 6 out of 15 plus without income $	Children under age 6 out of population 15 plus with no income [(V79/V1565*100)]
14.Percent in health occupations @	Population 15 plus in health out of all occupations [(V845/V829)*100]
15.Male employment Theil's T *	Male employment income -General Entropy (GE(1))
16.Female employment Theil's T**	Female employment income -General Entropy (GE(1)
17.Male after tax Theil's T^	Male after-tax income -General Entropy (GE(1))
18.Female after-tax Theil's T^^	Female after-tax -General Entropy (GE(1))
Gender Equality	
19.Unemployment rate sex ratio >	Male 15 plus unemployment rate to female 15 plus unemployment rate [(V606/V630]
20.Self-employment rate sex ratio $	Male 15 plus self-employed to female 15 plus self-employed [(V808/V820)*100]
21.Self-employment no help rate sex ratio $	Male 15 plus self-employed no paid help to female self- employed no paid help [(V809/V821)*100]
22.Unpaid family work $	Male unpaid family work to female unpaid family work [(V814/V826)*100]
23.Managerial occupation sex ratio $	Male 15 plus managerial to female 15 plus managerial [(V890/V950)*100]
24.Work at home sex ratio $	Male 15 plus work at home to female 15 plus work at home [(V1089/V1097)*100]
25.Child care sex ratio &	Male 15 plus look after children to female 15 plus look after children [(V1176/V1183)*100]
26.Prevalence low income before tax sex ratio $	Male 15 plus with low income before tax to female 15 plus with low income before tax [V1974/V1977]
27.Prevalence low income after tax sex ratio $	Male 15 plus with low income after tax to female 15 plus with low income before tax [V1975/V1978]
28.Science/engineering. education sex ratio@	Male 25 to 64 with science or engineering to female 25 to 64 with science or engineering [((V1214+V1215+V1216)/(V1227+V1228+V1229))*100]
29.Government transfer payment sex ratio $	Male 15 plus govt transfer payment to female 15 plus govt transfer payment [V1895/V1899]
Housing	
30.Household size &	Average number of persons in private households [V135]
31.House age ratio $	Ratio of houses constructed before 1960 to houses constructed after 1960 [((V110+V111)/(V112…V118)]
32.Percent one family households &	Percent one family households out of total private households [(V137/V136)*100]
33.Bedroom to room ratio &	Ratio of bedrooms to rooms per dwelling [V100/V99]
34.Households spending 30% plus @	Owner households spending 30% plus on major payments [(V2056/V2053)*100]
Education	
35.Percent 15-24 illiteracy &	Population 15 -24 with no certification or degree [(V1235/V1234)*100]
36.Percent 15-64 illiteracy &	Population 15 -64 with no certification or degree [(V1235+V1249)/(V1234+V1248)*100]
37.Percent 25-64 science/engineering education@	Population 25 -64 with science or engineering degree out of 25-64 with post-secondary [((V1214…V1229)/(V1208+V1221))*100]
38.Percent 25 to 64 post-secondary education&	Population 25- 64 with post-secondary to population 25 to 64 [(V1208 + V1221)/(V9_…+ V16+ V28+…+ V35)*100]
Ethnicity/Cultural diversity	
39.Percent immigrated before age 14 $	Population who immigrated before age 14 out of total immigrants [((V555+V556)/V478)*100]
40.Percent aboriginal population $	Population aboriginal out of total population [(V565/V564)*100]
41.Non-official language Theil's T#	Non-official language- General Entropy(GE(1)) (GE(1))[V3945/V3946)*(V1691/V1649)*(LN(V1691/V1649))]
42.Percent visible minority $	Population visible minority [(V1303/V1)*100]
43.Percent third generation &	Population 15 plus third generation or more [(V563/V1)*100]
44.Ethnic diversity	Ethnic diversity index [1-∑p_i^2]; pi=V1318/V1,...V1554/V1
Density/Infrastructure	
45.Population density >	The population density of each DA

46. Distance from city $^$	Area's distance (meters) to the nearest city
47. Percent walk or (motor)bike to work $^$	Population walk, bike or motor bike to work out of labour force 15 plus [(V1104+V1105+V1106)/V1100)*100]
48. Intersection density $^$	Intersection density (grid-style neighbourhood)
49. Cul-de-sac density $^$	Cul-de-sac density
50. Intersection cul-de-sac difference$^@$	Intersection minus cul-de-sac density

Source: Statistics Canada, 2006 Census

@ Square root transformation formula: New variable=SQRT (K-Old variable) where k=largest possible value+1
q Reflect square root transformation: New variable=SQRT(100+1-old variable)
$ Log 10 transformation: New variable=Log$_{10}$(old variable)

➢ Natural log transformation: New variable=Ln (1+old variable)
& No transformation

 * Male employment income − General Entropy (GE(1))= Male 15 plus for DA/Male 15 plus for Alberta)*(Male 15 plus employment income for DA /Male 15 plus income for Alberta)*(LN(Male 15 plus employment income for DA /Male 15 plus income for Alberta)

** Female employment income − General Entropy (GE(1))= Female 15 plus for DA/Female 15 plus for Alberta)*(Female 15 plus employment income for DA /Female 15 plus income for Alberta)*(LN(Female 15 plus employment income for DA /Female 15 plus income for Alberta)

^ Male after-tax income − General Entropy (GE(1))=(Male 15 plus for DA/Male 15 plus for Alberta)*(Male 15 plus after-tax income for DA/Male 15 plus after-tax income for Alberta)*(LN(Male 15 plus after-tax income for DA/Male 15 plus after-tax income for Alberta)

^^Female after-tax income − General Entropy (GE(1))=(Female 15 plus for DA/Female 15 plus for Alberta)*(Female 15 plus after-tax income for DA/Female 15 plus after-tax income for Alberta)*(LN(Male 15 plus after-tax income for DA/Male 15 plus after-tax income for Alberta)

Non-official language Theil's T=(DA's population/AB's population)*(DA's non-official mother tongue population/ AB's non-official mother tongue population)*LN((DA's non-official mother tongue population/ AB's non-official mother tongue population))