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Income Inequality and Health in Ontario: A Multilevel Analysis

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Income Inequality and Health in Ontario: A Multilevel Analysis

by

Guoliang Xi

Thesis submitted to the School of Graduate Studies and Research
in partial fulfillment of the requirements for the MSc degree in Epidemiology

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ABSTRACT

Objectives To examine the association of income inequality at the public health unit level with individual health in Ontario.

Design Cross sectional multilevel study. Individual-level data drawn from 30,939 respondents in Ontario Health Survey 1996-97. Median area income and income inequality calculated from 1996 census data, the latter using Gini coefficient.

Setting 37 public health units in Ontario.

Subjects Ontario residents aged 25 years or older.

Main outcome measures Self-rated health status and the Health Utility Index.

Results Controlling for individual-level factors, respondents living in public health units in the highest income inequality tercile had odds ratios of 1.25 (95% CI 1.10-1.42) for fair/poor self-rated health, and 1.14 (95% CI 1.04-1.25) for a Health Utility Index score < 1, compared with people living in public health units in the lowest tercile. Controlling further for median area income had little effect on the association.

Conclusions Income inequality was significantly associated with individual health status independent of individual income at public health unit level in Ontario.

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Chapter 1 Introduction

1.1 Background

Individual-level analyses have demonstrated a strong relationship between low socioeconomic status (SES) and overall mortality (Pappas et al., 1993), poor self-rated health (Heistaro et al., 1996), poor physical functioning (Hemingway et al., 1997), and cardiovascular disease risk factors (Winkleby et al., 1998). This result holds across a range of indicators of SES: income, education, and occupational status. Similarly, many studies have shown an association between poor neighborhood environments (deprived areas) and health indicators, such as increased admission rates to emergency department and high primary health care consultation rates (Andren et al., 1987; Sundquist et al., 1993), and high prevalence of self-rated poor health status and self-rated illness (Eachus et al., 1996). Beyond these indicators of absolute deprivation, there has long been an understanding that relative deprivation plays a role in indicating the quality of social environments (Runciman, 1966).

In the past decade or so, a growing number of studies suggest that the distribution of income — in addition to the absolute individual income and average area income — is a key determinant of population health. For example, higher income inequality at the state level in the United States has been associated with increased mortality in ecological studies (Kennedy et al., 1996; Kaplan 1996) and in multilevel studies of self-rated health (Kennedy et al., 1998; Soobader et al., 1999). However, findings are not entirely consistent across different studies and different countries. For example, other studies have failed to find an association between income inequality and health in the United States (Fiscella et al., 1997) and in Canada (Ross et al., 2000; Ramage-Morin, 2001). Also, the mechanism behind the association between income inequality and individuals' health is far from well-known, although Kawachi and others suggested that the association could be mediated in several ways (Berkman & Kawachi, 2000). Only a few studies have focused on this issue in Canada. This study examines the association between income inequality at the public health unit level and individual health in Ontario in the mid-1990s.

1.2 Literature Review

1.2.1 General

Throughout the world, economic, political, and technological processes have led to wealth and income becoming more concentrated. According to the 1996 Human Development Report (United Nations Development Program — UNDP, 1996), the world's 358 richest individuals controlled assets equivalent to the combined annual incomes of countries where 45 percent of the world's people live. The poorest 20% of the world's population saw their share of global income decline from 2.3% to 1.4% in the past 30 years. Meanwhile, the share of the richest 20% increased from 70% to 85%.

International comparisons have suggested that these inequalities in income have implications for health. Despite being the richest nation in the world, the United States lags behind other developed countries on many health indicators. For example, the USA has a gross domestic product per capita which is well over twice as high as that of Greece, yet life expectancy is higher in Greece than in the USA. According to the 1996 United Nations Development Report, the United States ranked 20th in life expectancy, lagging behind poorer countries such as Costa Rica, Greece, and Spain. This evidence suggests that beyond an economic threshold that determines basic necessities, continued economic growth has little relation to increases in life expectancy, and that income is related to health by mechanisms other than its role as a determinant of material living standards. In the United States, inequalities in the distribution of wealth are especially severe: the best-off one percent of the American population owns between 40 and 50 percent of the nation's wealth (Wolff 1995; Hacker 1997). Although lack of access to universal health care undoubtedly contributes to the poor health in the USA, growing evidence suggests that income inequality could have important implications for the health status of Americans.

1.2.2 Effect of Income Inequality on Health in Ecological Studies

Numerous ecological studies have provided support for this hypothesis, showing that unequal distributions of income are associated with mortality and life expectancy in populations both between and within nations.

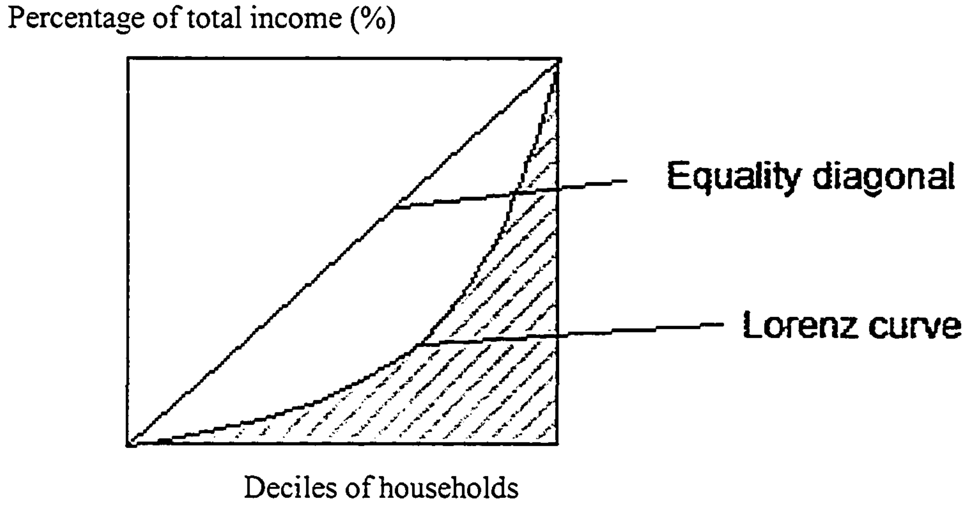
Rogers (1979) used data for 56 countries and found an association between income inequality and both infant mortality and life expectancy at birth, after taking Gross National Product into account. He found that the difference between a relatively egalitarian and a relatively inegalitarian country amounted to about 5 to 10 years in average life expectancy. Flegg (1982) investigated 59 mainly developing countries and found that income distribution was related to infant mortality, after controlling for a variety of factors. Le Grand (1987) reported that the share of national income going to the bottom 20% of the population was related to average age at death in a group of 17 developed countries, after controlling for Gross Domestic Product (GDP) and public and private expenditure on health care. Wilkinson (1986; 1990; 1992) has presented a number of different analyses for up to 15 developed countries, and has published a series of contributions in which he has argued that income distribution is the most important determinant of differences in average life expectancy.

There might be some limitations to these studies. For instance, data from different countries — especially on income distribution — may not be comparable in terms of quality or reliability. However, within-country ecological studies have provided similar evidence for the association between income inequality and health. For instance, in 1996, two American ecological studies reported that income inequality within that country was linked to poorer health outcomes (Kaplan et al., 1996; Kennedy et al., 1996). Kaplan et al. and Kennedy et al. both examined the relationship between the degree of household income inequality across the 50 US states and state-level variation in all-cause and cause-specific mortality. Kaplan et al. found a strong correlation ($r = 0.62$, $P < 0.001$) between income inequality (measured by the share of total income earned by the bottom 50% of households in each state) and age-standardized mortality rates; it was present in both men and women and in whites as well as African Americans. To see whether this was an artefact of the measures used, Kennedy et al. examined two other measures of income distribution: the Gini coefficient and the Robin Hood Index. Both measures were strongly correlated with age-adjusted total and cause-specific mortality rates. In regression models adjusting for poverty rates and median income, a 1% increase in the Robin Hood Index was associated with an excess mortality of 21.7 deaths per 100,000 (95% CI: 6.6 to 36.7), which suggests that even a modest reduction in inequality could have an important impact on public health.

1.2.3 Indicators of Income Inequality

Gini Coefficient: the Gini index is perhaps the most widely used measure of income distribution (Shyock, 1976). It is derived from the Lorenz curve, which is a graphical device for displaying the cumulative share of total income accruing to successive income intervals. In Figure 1, the curve shows the cumulative shares of income earned by successive deciles of households, arrayed in order from the bottom 10% upwards. If incomes were equally distributed, the Lorenz curve would follow the 45^0 diagonal. As the degree of inequality increases, so does the curvature of the Lorenz curve, and thus the area between the curve and the 45^0 line becomes larger. The Gini is calculated as the ratio of the area between the Lorenz curve and the 45^0 line to the total area below the diagonal. A difference of 0.01 between 2 Gini coefficients is considered significant (Rashid, 1998). See Shryock (1976:98) for details on calculation of the Gini coefficient and plotting of Lorenz curves.

Figure1 Lorenz curve



The Robin Hood Index: the Robin Hood Index (RHI) is equivalent to the maximum vertical distance between the Lorenz curve and the line of equal incomes, and represents the proportion of income that would have to be transferred from the richest half to the poorest half of the population in order to eliminate inequalities between them. A limitation of this measure is that redistributions of income among households that are on the same side of the median will not change the index. Kennedy et al. (1996) provide details on the calculation of the RHI.

Other indicators of income inequality are described in Appendix A.

1.2.4 Introduction to Multilevel Analysis

Ecological studies may have serious limitations because of the ecological fallacy — the assumption that group-level association hold at the individual level, when this is not true. Models using ecological data are more prone to model misspecification due to a greater likelihood of unmeasured confounding variables at the individual level. In other words, we should not assume that a relationship that occurs at group level can be held to exist at individual level. Studies examining differences between groups should take into account possible differences in group composition (i.e. characteristics of the individuals within them). In order to address this issue, a multi-level analysis is needed.

Multilevel models are developed for analyzing hierarchically structured data. Before elaborating on these models, more should be said about hierarchical data. A hierarchy consists of low-level observations nested within higher levels. Two-level examples include students nested within schools, employees nested within firms, or repeated measurements nested within persons. Many more levels can be thought of, such as students nested within classes, classes nested within schools, schools nested within neighborhoods, provinces, countries. Hierarchies exist everywhere. Analytical models that contain variables measured at different levels of a hierarchy are known as multilevel models. Multilevel analysis is an approach to the analysis of nested data including the statistical techniques as well as the methodology of how to use them. For a better understanding of multilevel analysis, the definitions of the terms contextual models, intra-class correlation, random and fixed coefficients, cross-level interaction, and iterative Generalized Least Squares (IGLS) and Restricted IGLS are summarized below.

Contextual Models: Traditionally, contextual models are defined as regression models containing two types of independent variables: individual-level variables and aggregated context variables, such as group means or medians. Contextual models are simple models in which variations at group level are not allowed. Hence they are fixed-effects models.

Intra-class Correlation (ICC): The intra-class correlation is a measure of the degree of dependence of individuals. The more individuals share common experiences due to closeness in space and /or time, the more they are similar. For example, the highest degree of dependency can be found between monozygotic twins raised in the same family. To acknowledge the existence of an intra-class correlation is important because it changes the error variance in standard linear regression. A small intra-class correlation can inflate the significant alpha level substantially (Kreft & Leeuw, 1998). ICC is an important issue in analysis of complex surveys that used cluster sampling.

More specifically, in a two-level multilevel linear regression model, ICC is defined as the proportion of the total variance in the outcome variable that occurs between the higher level units, and is given by:

$$\rho = \frac{\tau_0^2}{\tau_0^2 + \pi^2 / 3}$$

where τ_0^2 is the variance between groups; and $\pi^2 / 3 = 3.29$ (Snijders and Bosker, 1999).

Fixed versus Random Coefficients: For multilevel analysis involving two levels, the model can be conceptualized as a two-stage system of equations in which the individual-level variation within each group is explained by an individual-level equation, and the variation across groups in the group-specific regression coefficients is explained by a group-level equation (Diez-Roux, 2000). In the first stage, the units of analysis are individuals. For a two-level linear model,

Equation 1: $Y_{ij} = b_{0j} + b_{1j}I_{ij} + e_{ij} \quad e_{ij} \sim N(0, \sigma^2)$,

where Y_{ij} = outcome variable for ith individual in jth group (or context) and I_{ij} = an individual-level variable for ith individual in jth group (or context). For a multilevel linear regression model, individual-level variations (e_{ij}) within each group are assumed to be independent and normally distributed with a mean of 0 and a variance of σ^2. For a multilevel logistic regression model, the individual-level variations (e_{ij}) are assumed to have a binomial distribution. The same regressors are generally used in all groups, but regression coefficients (b_{0j} and b_{1j}) are allowed to vary from one group to another (hence the subscript j for these coefficients).

In the second (higher) stage, each of the group- or context-specific regression coefficients defined in equation 1 (b_{0j} and b_{1j} in this example) is modeled as a function of group-level variables. In this second stage, the units of analysis are groups.

Equation 2: $b_{0j} = \gamma_{00} + \gamma_{01}C_j + \mu_{0j} \quad \mu_{0j} \sim N(0, \tau^2_{00})$,

Equation 3: $b_{1j} = \gamma_{10} + \gamma_{11}C_j + \mu_{1j} \quad \mu_{1j} \sim N(0, \tau^2_{11})$,

$\mathrm{cov}(\mu_{0j}, \mu_{1j}) = \tau^2_{10}$,

where Cj is a group-level or contextual variable.

The residuals in the group-level equations (μ_{0j} and μ_{1j}) are assumed to be normally distributed with mean 0 and variances τ^2_{00} and τ^2_{11} respectively. μ_{0j} measures the unique deviation of the intercept of each group from the overall intercept, γ_{00}, after accounting for the effect of C_j. Analogously, μ_{1j} represents the deviation of the slope within each group from the overall slope, γ_{10}, also after controlling for the effect of C_j. τ^2_{00} and τ^2_{11} are the variances of the group intercepts and group slopes, respectively. τ^2_{10} represents the covariance between the intercepts and slopes. An alternative way to present the model fitted in multilevel analysis is to substitute Equations 2 and 3 in Equation 1 to obtain:

$$Y_{ij} = \gamma_{00} + \gamma_{01}C_j + \gamma_{10}I_{ij} + \gamma_{11}C_j I_{ij} + \mu_{0j} + \mu_{1j} I_{ij} + e_{ij}.$$

The model includes the fixed effects of group-level variables (γ_{01}), individual-level variables (γ_{10}), and their interaction (γ_{11}) on the individual-level outcome Y_{ij}. The coefficients in the fixed part in multilevel models are similar to the coefficients in standard single-level models. They can be used to estimate the independent effects of group-level variables, individual-level variables and their interaction on individual-level outcomes. The model also includes a random intercept component (μ_{0j}), a random slope component (μ_{1j}), and the individual-level variations (e_{ij}). The random part can be used to estimate variations between groups and calculate the intra-class correlation coefficient.

Cross-level Interaction (γ_{11}): Cross-level interactions are defined as interactions between variables measured at different levels in hierarchically structured data. An example is the interaction between student characteristics and teacher characteristics. Effective teachers may only be effective with certain types of students, not necessarily with all students. If certain teachers are, for instance, more effective with bright students than with others, this means that relationship between an individual student's aptitude and achievement is strengthened by such a teacher.

IGLS and RIGLS: Various algorithms are available to determine the estimates in multilevel analysis. They have names such as IGLS (Iterative Generalized Least Squares and RIGLS (Restricted IGLS). IGLS is used in multilevel linear regression, while RIGLS is used in multilevel logistic regression. They are iterative, which means that a number of steps are taken in which a provisional estimate comes closer and closer to the final estimate. When all goes well, the steps converge to the final estimates.

1.2.5 Rationale for Multilevel Analysis

The idea that individuals may be influenced by both individual factors and their social context is a key notion in the social sciences (Blalock, 1984; DiPrete et al., 1994). It is important to distinguish between compositional and contextual differences. A compositional effect would attribute differences to the fact that areas include different types of individuals, and the differences between these individuals account for the observed difference between areas. For example, if low socioeconomic status (SES) people have poorer health than high SES people, it would not be surprising if areas with many low SES people have, on average, poorer health. Hence the observed difference between areas may be due to concentration of poor people in these areas, and health outcomes therefore a property of individuals, not of areas. A contextual effect would hold that there are features of the social or physical environment that influence the health of those people "exposed" to it, that is, similar types of individuals may have different types of health outcomes in different types of areas. For example, poor people living in advantaged areas may have different health outcomes from poor people living in disadvantaged areas, and people whether rich or poor might live longer if they live in non-polluted areas with a pleasant climate and an excellent range of services (Berkman and Kawachi, 2000). It is important to keep in mind the distinction between these compositional and contextual effects because they are often confused in studying area variations in health.

In acknowledging the existence of both compositional and contextual effects, it becomes apparent that health outcomes are associated with processes operating at more than one level: a lower level compositional effect and a higher level contextual one. To gain a more complete understanding, all the relevant levels of analysis need to be considered simultaneously, but this requirement poses serious technical difficulties for traditional statistical modeling techniques which operate only at a single level.

When analyzing data relating to individuals nested within groups, if we ignore group membership and focus on individual-level attributes (compositional effect), we ignore the potential importance of group-level attributes in influencing individual level outcomes (contextual effect). In addition, if outcomes for individuals within areas are correlated, the assumption of independence of subjects is violated, resulting in incorrect standard errors and inefficient estimates (Hox, 1995).

Contextual models, in which both individual-level and group-level independent variables are considered, are not new, but multilevel models are newer and more general. Because contextual models are not able to consider variations at group level, inferences are made only on the basis of the groups explicitly studied (fixed effect models) and not to the wider population from which they are drawn, making this approach both unrealistic and limited.

By quantifying the variability between groups, multilevel models allow estimation of group-level variability and how it changes as individual-level variables and group-level variables are added. In addition, the inclusion of these variations allows for the possibility that individuals' outcomes within groups may be correlated, even after accounting for the individual-level and group-level variables in the model. By taking into account this correlation, multilevel models correctly estimate the standard errors associated with the regression coefficients. Also, the allowance for variation in the group level may be especially appropriate if groups can be thought of as a sample of a larger population of groups about which inferences are to be made (Snijders and Brosker, 1999; Diez-Roux, 2000).

Over the past few years, multilevel analysis has emerged as a new analytical strategy, allowing the simultaneous examination of group-level and individual-level factors. The statistical issues involved in multilevel studies have been well described (Snijders and Brosker, 1999; Hox, 1995) and multilevel regression analysis is becoming widely accepted as the appropriate tool for examining group level effects on individual health.

1.2.6 Studies of Income Equality on Health Using Multilevel Analysis

Several studies have examined the association between inequality of income and health, using multilevel methods. In 1997, Fiscella and Franks (1997) found that income inequality at community level was correlated with population rates of mortality ($r = 0.34$, $p = 0.04$); However, when community income inequality was examined simultaneously with individual income, the relationship between community income inequality and individual risk of death disappeared ($p = 0.75$); meanwhile individual income remained powerfully predictive of mortality risk ($p < 0.01$).

More recently, Daly et al. (1998) found that inequality had statistically significant detrimental effects on mortality risk among non-elderly (ages 25-64), or middle-income individuals, even after adjustment for individual income. Kennedy et al. (1998) examined the relationship between state-level income equality and individual self-rated health, based on a large sample size ($N = 205,245$ individuals residing in 50 states). The results of the multilevel analysis indicated a modest, but statistically significant, deleterious effect of income inequality on self-rated health. Stronger associations were found between low household income and self-rated health (odds ratio = 3.47, comparing individuals earning less than $10,000 to those earning more than $35,000). When the analyses were stratified by individual income level, the deleterious effects of inequality were most evident among individuals with the lowest income (multivariate adjusted odds ratio for fair-poor health, 1.33; 95% CI, 1.22-1.45, comparing the highest to lowest inequality states within strata of individuals earning less than $ 20,000 per year).

Lochner, Pamuk, Makuc, Kennedy, and Kawachi (2001) conducted a multilevel study of the association of state-level income inequality with mortality using the U.S. National Health Interview Survey respondents for 1987-94, followed up for mortality to 1995. They found an approximately 10% (and statistically significant) lower mortality risk in the 10 lowest income inequality states compared to the remaining states.

1.2.7 Critique of Studies Linking Income Distribution to Health

Reflecting these inconsistent findings, some authors (e.g., Judge, 1995; Saunders; 1996) have questioned the evidence for the positive association between income inequality and health. Several criticisms of the evidence have been mentioned. First, different studies used different indicators to measure income inequality, and the choice often appears to have been arbitrarily made. In other words, does the choice of indicators matter? Second, the household data used to derive the income inequality measures were not adjusted for taxes and transfer payments. Third, the household income data were not adjusted for household size. Each of these will be discussed in turn.

Does the choice of indicator matter? Kawachi and Kennedy (1997) used a cross-sectional design study to test the relationships of six different income inequality indicators to total mortality rates in the 50 U.S. states. The six different indicators were: the Gini coefficient; the decile ratio; the proportions of total income earned by the bottom 50%, 60%, and 70% of households; the Robin Hood Index; the Atkinson Index; and Theil's entropy measure (Appendix A). All were highly correlated with each other (Pearson $r \geq 0.94$), and all were strongly associated with mortality (Pearson r ranging from 0.50 to 0.66), even after adjustment for median income and poverty. Thus, the choice of income inequality indictors does not appear to alter the conclusion that income inequality is linked to higher mortality.

Adjustment of household incomes for taxes, transfer payments and household size. Judge (1996) has argued that to the extent that taxes and transfer payments redistribute incomes, failure to adjust for them will overstate the extent of income inequality between households. Adjusting for taxes and transfer payments is especially important in cross-national comparisons, since countries vary a great deal in their redistributive policies. However, in the context of within-country or within-province studies, evidence suggests that taxes and transfer payments have a modest impact on income distribution. Whether adjusting for household size would alter the income inequality/mortality relationship was tested by Kawachi and Kennedy (1997) using household micro-data provided by the Luxembourg Income Study. After simultaneously adjusting for taxes, transfer payments, and household size, the relationship between income inequality and mortality rates was virtually unchanged ($r = 0.54$ using the adjusted Gini coefficient, compared to $r = 0.51$ using unadjusted Gini). In summary, the income inequality/mortality link could not be explained away by failure to use an adjusted income inequality indicator.

1.2.8 Studies of Income Equality on Health In Canada

Most of these studies were from the United States. What were the major findings in this area in Canada?

In 1998, Boyle and Willms (1998) estimated the effects of place on the distribution of health problems, health-related quality of life, general well-being, and family functioning, using a multilevel approach. Statistically significant variations between Ontario Public Health Units were found even after adjustment for individual-level factors like age, education, marital status and household income, although they were very small.

Ross et al. (2000) found that there were significant associations between income inequality and mortality in the United States, whereas such associations were not apparent in Canada at either the provincial or metropolitan area levels. They argued that Canada and the United States have some major differences, especially with regard to social policy. US metropolitan areas differ greatly from Canadian metropolitan areas in terms of the degree of economic and social inequality they generate and the ways in which unequal material circumstances and social relations are institutionalised through policy and urban political structure. Although economic segregation and social polarization are less pronounced in Canadian cities, some studies have suggested that they increased in the last generation (Yalnizyan, 1998). For example, the market income ratio of the top 20% of families with children under 18 to the bottom 20% of such families increased from 8.52 in 1980 to 18.65 in 1996, so the current picture of no impact of inequality in Canada may change in the future.

Ross and Wolfson's study used mortality as an outcome. The present study uses morbidity variables such as self-rated health status (SRH) and the Health Utility Index (HUI).

1.3 Objective of This Study

Primary objective: To examine the effect of income inequality at the level of Ontario public health units (PHUs) on individual-level health as measured by self-rated health status and the Health Utility Index, using a cross sectional multilevel study, while controlling for other PHU-level variables (e.g., median area income) and individual-level variables (e.g., individual income, smoking, education, marital status).

Secondary objective: To examine whether the relationship between health measures and income inequality differs by individual income.

Hypotheses

1. All other things being equal, an individual's health status is better in an area with a more equal distribution of incomes.

2. Individual biological and behavioral factors cannot fully explain the difference in health outcomes between the Ontario PHUs.

3. The effects of income inequalities on health are different in poor and rich people. For instance, there may be a stronger effect of income inequality on poor people's health.

Chapter 2 Materials and Methods

2.1 Sources of Data

2.1.1 Area-level Data

Data on area characteristic variables such as median area income came from the 1996 Census (Statistics Canada, 1999). These were grouped geographically into the areas of the Ontario public health units. The reasons for choosing public health units as boundaries were: 1) public health units would not be too small in terms of variation in income distribution and population size; 2) public health units are often the focal points for governance and resource allocation, and frequently come with an information base useful for characterizing the sociodemography of inhabitants (see below, on Ontario Health Survey). The availability of such information is a powerful incentive for studying places that serve administrative objectives (Boyle & Willms, 1999).

2.1.2 Individual-level Data

Data on individuals aged 25 or older were drawn from the Ontario Health Survey 1996-97, which was an expansion of the National Population Health Survey 1996-97 (NPHS). The NPHS was conducted by Statistics Canada; methods used in the survey have been detailed elsewhere (Statistics Canada, 1997). In brief, the target population included household residents in all provinces, with the principal exclusion of residents of Indian reserves, Canadian military bases, and some remote areas in Quebec and Ontario. The survey included questions related to the determinants of health (e.g., socioeconomic status, smoking, body weight, height, and household composition), health status (e.g., self-rated health status and derived variables like the Health Utility Index), and use of health services.

Subjects aged 25 or older were selected for this analysis for the following reasons: 1) educational attainment would often not be completed at younger ages, and educational attainment and individual income are highly associated with self-reported health status; 2) younger ages may have no income because they would not be in the labor force; and 3) younger ages generally have good health: the percentage of poor/fair self-reported health status for those aged less than 25 years was only 4.4%, providing little variability.

The Census data (1996) and Ontario Health Survey data (1996-97) were provided by the Health Information Partnership, Eastern Ontario Region (HIP).

2.1.3 Sample Selection

The NPHS sample design was a stratified two-stage design (Statistics Canada, 1997). In the first stage of sampling, each province was divided into three types of areas (major urban centers, urban towns, and rural areas), within which separate geographic and/or socio-economic strata were formed. In each stratum, six clusters (primary sampling units or PSUs), usually census enumeration areas (EAs), were selected with probability proportional to size (PPS) sampling. In the second stage, dwellings were systematically selected from dwelling lists within each cluster.

Ontario chose to increase its allotted NPHS sample size through the buy-in of additional cross-sectional units in the second cycle (1996-97). The supplementary sample sizes were allocated according to health areas determined by the provincial Ministry of Health. All of these interviews were done by telephone, using the Statistics Canada Random Digit Dialing (RDD) system. In this system, telephone exchanges (the first three digits of the telephone number) were used as stratification units and strata were composed of groups of exchanges that covered the same health areas. Each of the 23 health areas required a total of 1,200 health component respondents who agreed to share their data with the Ministry of Health. Exceptions to this rule occurred in the health areas covering Toronto and Ottawa. In these health areas the required number of respondents was 3,000 and 2,000, respectively.

There are some limitations to RDD sampling. First, although telephone coverage is very high in Canada at 97%, non-coverage is higher for rented houses, single person households, low-income households, and those with unemployed persons, and is slightly higher outside major urban areas (Trewin & Lee, 1988). RDD interviews also cannot usually access some types of people such as street people. In addition, non-response tends to be more problematic for telephone interviews because of unanswered phones, difficulties finding respondents at home, and the increased use of call screening.

Response Rate: The response rate in Ontario was 78.8%. Non-response in the NPHS was minimized using a number of approaches (Statistics Canada, 1997). For example, when a household could not be reached, numerous call attempts or visits were made at various times of the day. In cases where an individual refused to participate, a letter was sent from the Regional Office, which stressed the importance of the survey and the household's co-operation. All non-response cases were also followed-up in subsequent data collection periods, with an additional collection held in June 1997 in a final attempt to reach households.

Weighting: Survey weights can be used to represent the probability that a particular individual is sampled. In single-stage sampling, the sample weight is defined as the inverse of the individual's inclusion probability, which is the probability that person will be included in the sample. In multi-stage sampling, the inclusion probability is the product of the PSU-level inclusion probability from the first stage of sampling, and the conditional inclusion probability from the second stage (Korn & Graubard, 1999). For provinces like Ontario with RDD supplement samples, the sample weight was based on the probability of selecting that telephone number using stratified simple random sampling without replacement. These weights were adjusted for household and household member non-response and post-stratified using strata based on health area, age, and sex (Statistics Canada, 1997). Use of sampling weights should give accurate point estimates for regression coefficients (Korn & Graubard, 1995).

Design effect: Statistical tests usually assume that each individual in the sample was selected independently of other individuals in the population being studied. The NPHS used a complex sample design that did not meet this assumption. The complex survey design effectively reduces the actual sample size by approximately the square root of the design effect which is the ratio of the true variance to the variance calculated on the assumption of simple random sampling (Snijders and Bosker, 1999), The variances obtained will therefore be underestimates of the true variances, leading to confidence intervals that are too narrow and p-values that appear more significant than they truly are, e.g., inferring that an effect is statistically significant when it is not (Goel V., Analysis of complex surveys. Institute for Clinical Evaluative Sciences, unpublished manuscript, 1993). An appropriate approach, which is strongly recommended by Statistics Canada, is the use of the bootstrap method to compute all measures of precision, such as variances, standard deviations, etc. NPHS provides its users with a SAS macro program that facilitates the calculations of variances for some types of analysis (measures of totals and ratios, linear and logistic regression). However, it is not feasible to combine multilevel analysis with the bootstrap method in the same model. Multilevel analysis was chosen in the present study.

Data release: Statistics Canada issues detailed guidelines for release of estimates (e.g., prevalence of disease) based on NPHS results. These relate to two issues: precision of estimates and confidentiality of individuals. These issues are influenced by both the numbers of respondents interviewed and the sample design. The OHS was designed to produce estimates for 23 "local health areas", but 23 is rather few for conducting multilevel analysis (recommendations in the literature are usually for 30 or more). Public use microdata files have been modified to protect confidentiality, and do not contain any address information below the health area level. The data for this study were obtained from HIP, which has access to files containing more detailed address information. We have therefore been able to conduct the analysis at the level of the 37 (reduced from 42) public health units. The only NPHS-based estimates we present for individual PHUs are for self-rated health and HUI < 1 in persons aged 25+, so confidentiality is not threatened. The precision of these estimates meets the criteria for release. The available sample sizes far larger than are required for multilevel analysis (30 per area). There remains a question of whether the sample design provides a representative sample for the public health units, but we were advised that it was probably acceptable (Douglas Yeo, personal communication, 2001 July 27).

2.2 Methods

2.2.1 Study Design

This study included 37 public health units (treating Toronto as one unit as described in Section 3.1) and used a cross sectional multilevel design, in which the effects of area-level factors and individual-level factors on health could be examined simultaneously.

2.2.2 Dependent Variables

Self-rated Health Status (SRH): Information on the dependent variable, self-rated health status, was given by the respondents in answer to the NPHS question "In general, how would you say your health is?" There were 5 possible responses: excellent, very good, good, fair, or poor. We created a dichotomous outcome measure that equaled 1 if the respondent answered fair or poor, and 0 if good, very good or excellent (this cutoff point is used in most published articles using a dichotomized version of SRH).

The Health Utility Index: The Health Utility Index (HUI) is a health status index that provides a utility weight between 0 and 1 for an individual's functional capacity. The index, developed at McMaster University's Centre for Health Economics and Policy Analysis, is based on their Comprehensive Health Status Measurement System (CHSMS). It provides a description of an individual's overall functional health, based on eight attributes: vision, hearing, speech, mobility (ability to get around), dexterity (use of hands and fingers), cognition (memory and thinking), emotion (feelings), and pain and discomfort (Torrance et al., 1992). The resulting HUI provides a single numerical value (between 0 and 1) for any possible combination of levels of these eight self-reported health attributes. For instance, an individual who is near-sighted, yet fully healthy on the other seven attributes, receives a score of 0.95 or 95% of full health. Such a measure can be used for health policy evaluation and for the assessment of health care interventions at the population or the clinical level.

Because the HUI scores were not normally distributed even after logarithmic transformation, we created a dichotomous outcome measure equal to 1 if the HUI was less than a perfect score 1. In addition, we also tried a different cut-point (50th percentile) to see whether the association between income distribution and health still holds.

Other outcomes: we also tried other outcome variables including bronchitis, chronic conditions, two-week disability, heart disease, high blood pressure, and diabetes. Information on these dependent variables was given by or derived from the respondents in answer to NPHS relevant questions. For example, information on heart disease was based on the question: " Do you have heart disease diagnosed by a health professional? ". We created a dichotomous outcome measure equal to 1 if the respondent answered "yes", 0 if "no" for each such variable. For derived variables like number of chronic conditions, we created a dichotomous outcome measure equal to 1 if the respondent reported two or more chronic conditions, 0 if the respondent reported no or 1 condition. For heart disease, we conducted the analysis restricted to those aged 40 or older, because those aged from 25 to 39 years had a low percentage of heart disease (0.9%).

2.2.3 Independent Variables

Area-level Variables: We used the Gini coefficient as an indicator of income inequality within a public health unit. See Appendix B for details.

The Gini coefficient is highly correlated with other measures of income inequality (Kawachi & Kennedy 1997), evaluates inequality right across the income range, and is the most commonly used measure of income inequality. The Gini ranges theoretically from zero (absolute equality) to 1.0 (absolute inequality in the distribution of income). The 1996 Census provides annual household income data for 11 income intervals. Counts of the number of households falling into each income interval along with the total aggregate income were obtained for each of 37 Ontario public health units.

We did not adjust for taxes because this kind of information is not available in the Census. Other area-level variable included median area income, which was calculated for each PHU from pooled county data for households in the 1996 Census.

Public health units were assigned to three equal-sized categories of income inequality on the basis of the distribution of the Gini coefficients across 37 PHUs; see table 3.4 in chapter 3 for details on the results of Gini.

Category 1 (Gini   0.36) represents the PHUs with small inequalities in income. This included 13 PHUs: Durham, Peel, Perth, Oxford, Halton, Leeds-Grenville-Lanark, York, Haldimand-Norfolk, Wellington-Dufferin-Guelph, Elgin-St. Thomas, Renfrew, Simcoe, and Huron.

Category 2 (Gini: 0.36-0.38) included 12 PHUs: Thunder Bay, Haliburton-Kawartha-Pine Ridge, Northwestern, Muskoka-Parry, Brant, Hasting-Prince Edward, Chatham-Kent, Lambton, Bruce-Grey, Eastern Ontario, Waterloo, and Niagara.

Category 3 (Gini   0.38) represents the PHUs with the greatest inequalities in income: Peterborough, Porcupine, Ottawa-Carleton, Kingston-Frontenac-Lennox-Addington, Windsor-Essex, Middlesex-London, North Bay, Sudbury, Hamilton-Wentworth, Algoma, Timiskaming, and Metro Toronto.

Individual-level Variables: Individual-level data selected from the survey included information on age, sex, smoking habits, individual income, educational level, marital status, and physical activity. All of these individual factors are known to be associated with health status. Also, these variables are commonly used in other studies, and information on these variables is available in the OHS.

Smokers included current smokers and ex-smokers. Current smokers were respondents who reported smoking cigarettes every day at the time of the survey. Ex-smokers were those who reported smoking cigarettes daily in the past, but who were not smoking at the time of the survey. Marital status was dichotomized into married and unmarried, with the latter including persons who were widowed, divorced, separated, or never married. Education attainment was categorized as less than post-secondary, or equal or higher than post-secondary. Income adequacy was represented as annual household income adjusted for the number of household members according to Table 2.1 (Statistics Canada, 1997). The subjects were classified into low-, middle-, and high-income groups, with the middle-income group combining lower middle income and upper middle income.

Table 2.1 Definition of income adequacy, Ontario Health Survey 1996-97

CODE	DESCRIPTION	INCOME	HHSIZE
1	Lowest income	Less than S15,000	1 or 2 persons
		Less than S20,000	3 or 4 persons
		Less than S30,000	5 or more persons
2	Lower middle income	S15,000 to S29,999	1 or 2 persons
		S20,000 to S39,999	3 or 4 persons
		S30,000 to S59,999	5 or more persons
3	Upper middle income	S30,000 to S59,999	1 or 2 persons
		S40,000 to S79,999	3 or 4 persons
		S60,000 to S79,999	5 or more persons
4	Highest Income	S60,000 or more S80,000 or more	1 or 2 persons 3 persons or more
9	Unknown	Not stated	Not applicable

Other variables included in the analysis were age (25-39, 40-64, or 65 years), sex, and regular exercise (yes, no).

2.2.4 Sample Size and Study Power

Sample size and power calculation for multilevel hypotheses testing are particularly complex. Power depends both on the number of groups and on the number of individuals per group. The power to estimate between-group variability and group-level effects is strongly dependent on the number of groups included in the analysis (Langford, 1994). The power to detect cross-level interactions was studied by Bassiri (1988) and by van der Leeden and Busing (1994). Both studies showed that to obtain sufficient power to detect cross-level interactions at least 30 groups, and 30 observations within each group, are needed. Our sample size met this requirement.

2.2.5 Statistical Analysis

The sample for analysis included all Ontario respondents aged 25 years and older who responded to self-administered questionnaires. First, we conducted preliminary analysis to evaluate the utility of the outcome measures, the aggregation of areas, and the value of certain independent variables. We used standard single-level logistical regression to see whether income inequality was significantly associated with the various health outcomes. This is a reasonable first step, since we believe that the point estimates of the standard single-level method would differ little from those of multilevel analysis (Hox, 1995).

The definitive analysis comprised 4 steps:

1. Description of the distribution of the selected variables and the respondents by level of income inequality (Gini coefficients).

2. Calculation of the age-standardized prevalence (by the direct method) of poor/fair self-rated health status (SRH), and the Health Utility Index score less than 1, and presentation by income inequality category.

3. Correlational analysis: calculation of Pearson correlation coefficients for the relationship between age-standardized prevalence of the two outcomes and the Gini coefficients for the 37 Public health units, respectively.

4. Multilevel Analysis

The data were analyzed using the software package MLwiN version 2.1a (Rasbash et al., 2000), because of their hierarchical nature. Multilevel logistic regression models were applied to examine the relationship between income inequality and poor/fair self-rated health, and the Health Utility Index (score<1 or

50th percentile), while controlling for a range of individual-level factors that predict health, including age, sex, smoking status, individual income, education attainment, physical activity, and marital status, and the area-level factor median area income. The method of estimation is restricted iterative generalized least squares (RIGLS). Odds ratios and 95% confidence intervals for each of the health measures in relation to income equality were estimated. Joint Wald tests (two-sided) were used to test the significance of estimates in the fixed parts of the models, including interactions of the Gini coefficient with each covariate at the two levels. For the random parts of the models, the tests are one-sided because variances are by definition non-negative. Relative weights were used in the analysis. The relative weights were defined as the population weights divided by the average weights for responses from all the subjects (V. Goel, Analysis of complex surveys. Institute for Clinical Evaluative Sciences, unpublished manuscript, 1993). Use of these sampling weights should give accurate point estimates for regression coefficients.

A three-step sequential modeling strategy was adopted, with complexity being increased in each successive model. The modeling strategy was governed by the need to illustrate the advantages that arise as a result of adopting a multilevel approach. While a large number of models could be estimated, only those that are particularly important and relevant to the association between income inequality and health are reported. The models were described as follows:

Empty Model: A two-level model with only a constant term in the fixed and the random parts. Between-area variation in poor health is displayed and provides a base for further comparison, particularly of the contextual variation (null multilevel model). The intra-class correlation coefficient could be estimated at this step.

Model 1: Like the empty model, but considering all the individual predictors in the fixed part. This model assessed the relationship between poor health and all the individual predictors. Variation between the PHUs was allowed for, conditional on individual, compositional factors ('random-intercepts' model).

Model 2: Like Model 1, but included area-level variables. In this way, the extent to which area characteristics account for variation between PHUs was estimated. Interactions between different income groups and income inequality were also considered.

Since the response variable is binary outcomes, logistic multilevel models based on a logit-link function were used (Goldstein, 1995). The logistic regression model using logarithm transformation is a model where the logit (p) is a linear function of the explanatory variables, and its range is from minus infinity to plus infinity. The general term for such a transformation function is the link function, as it links the probabilities (or more generally, the expected values of the dependent variable) to the explanatory variables.

Models were fitted using second-order penalized quasi-likelihood estimation procedures (PQL) under the RIGLS estimating method in MLwiN. Marginal quasi-likelihood (MQL) and penalized quasi-likelihood (PQL) are the two approximation procedures for multilevel regressions. Both of them rely on the Taylor expansion to achieve the approximation. When the approximation is around the estimated fixed part, this is called MQL; when it is around an estimate for both fixed and random parts it is called PQL. Using MQL procedures may lead to a downwardly biased estimate of the level-2 variance, so it is advisable to use PQL methods. Also, the second-order MQL and PQL are expected to yield more accurate estimates than the first-order ones because they use some of the second-order terms in the Taylor expansion (Goldstein & Rasbash 1996). For detailed description of the use of these procedures see their paper.

For discrete dependent variables, the variance at the individual level was set to 1, corresponding to the assumption of no extra-binomial variation, and this assumption was tested in each logistic regression model. No evidence was found for extra-binomial variation. Evidence of extra-binomial variation could be due to omission of an important level 1 explanatory variable, omission of a higher level in the model, or incorrect specification of the link function (Snijders and Brosker, 1999).

The results from the multilevel analysis were compared with those from traditional analysis (contextual models), in which we assumed that individuals within groups are independent. Moreover, we also used a SAS Glimmix macro (Ramon et al., 1996) to replicate the multilevel analysis to see whether the results would be different from those from MLwiN.

Chapter 3 Results

3.1 Preliminary Analyses

1.Health Outcomes. The results of the single-level logistic regression after adjusting for the 7 individual-level factors (age, sex, education, marital status, physical activity, individual income, and smoking) are presented in Table 3.1.

As can be seen, there were no significant associations between income inequality and these outcomes except self-rated fair/poor health (SRH) and less than perfect health (HUI<1). Hence we concluded that only SRH and the HUI should be further investigated and reported.

Table 3.1 Associations of health outcomes with PHU-level income inequality, Ontario Health Survey 1996-97

Health Outcomes	Gini	OR	95%CI
Self-rated fair/poor health	Low	1.00	
	Medium	1.16	1.04-1.29
	High	1.20	1.10-1.31
Less than perfect health (HUI<1)	Low	1.00	
	Medium	1.11	1.03-1.20
	High	1.09	1.03-1.16
Bronchitis	Low	1.00	
	Medium	1.18	0.98-1.42
	High	1.06	0.90-1.24
Chronic Conditions (2 or more)	Low	1.00	
	Medium	1.05	0.98-1.13
	High	0.95	0.90-1.01
Two-week Disability	Low	1.00	
	Medium	1.03	0.93-1.14
	High	0.99	0.91-1.07
Heart Disease (Aged 40+)	Low	1.00	
	Medium	1.06	0.91-1.23
	High	1.00	0.88-1.13
High Blood Pressure	Low	1.00	
	Medium	0.88	0.80-0.98
	High	0.95	0.87-1.03
Diabetes	Low	1.00	
	Medium	0.90	0.76-1.06
	High	0.99	0.86-1.13

Note: odds ratios are from a weighted single-level logistic regression model after adjusting for 7 individual-level factors (age, sex, education, marital status, physical activity, individual income, and smoking).

2. Aggregation of Areas. We also tried to assess the association between income inequality and self-rated health at two different levels (e.g., 23 local health areas and 49 counties). The results from the multilevel fully-adjusted model (model 2)

showed that the association at county level was not as strong as that at public health unit level. Although the estimates of the association at local health area level was similar to those at public health level, there are only 23 such areas, which would reduce the power to test cross-level interactions in the multilevel models. Furthermore, it seems likely that the three area levels are not significantly different, since the boundaries of some areas are the same across the three area levels (e.g., Ottawa-Carleton Region). Hence we chose the results at PHU level to report. When the OHS was conducted, Metropolitan Toronto was divided into 6 PHUs. We were concerned that cutting it into several small areas might not allow income inequality to exert an independent effect on health in terms of variations in income distribution. We think that relatively natural geographic boundaries should be used rather than artificial ones in terms of the association. Indeed, when cutting Toronto into four sub-areas (i.e., Toronto-East York-York, North York, Scarborough, and Etobicoke), we found that the association was weakened. We treat Toronto as one area in the analysis.

3.Body Mass Index (BMI): there were 6,635 subjects aged 65 and older in the OHS 1996-97, for whom BMI data were missing because the questions about weight and height were not asked for that age group. We conducted the analysis restricted to those aged 25-64 years with BMI and to those aged 25 or over without BMI, respectively. Excluding the variable BMI had no effect on the effects of income inequalities, although BMI itself had a strong effect on health. Hence, the variable BMI was excluded from the analysis.

4. Racial Division: Of the 30,820 respondents used in the analysis for SRH, 92.4% were white, only 1.6 % and 5.6% were black or other races, respectively. Also, there were 10 public health units where no blacks were sampled. It prevented us from testing whether racial divisions had an effect on the association between income inequality and health.

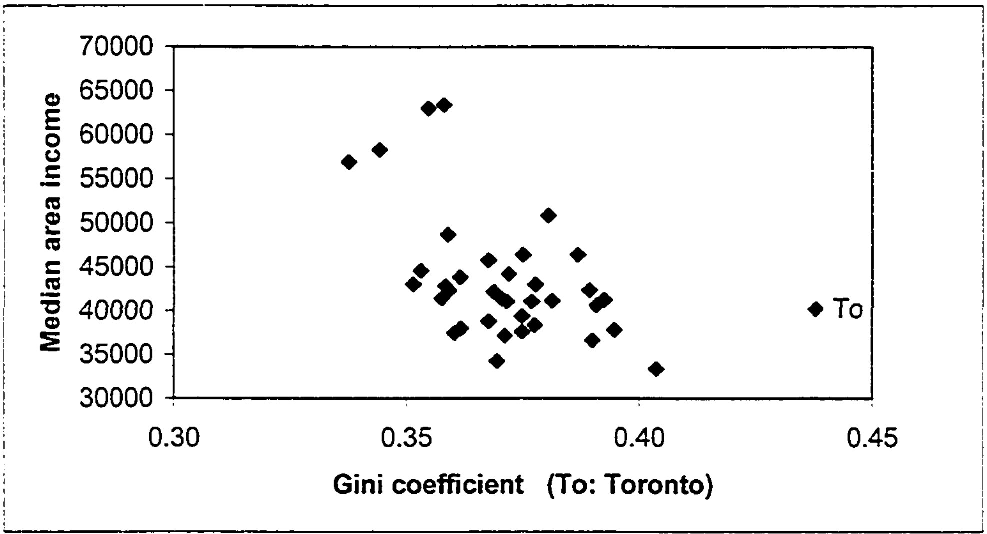
3.2 Description of the Sample

The Ontario Health survey sample consisted of 36,892 individuals. The 30,939 people aged 25 or older were selected for this study (45.9% male and 54.1% females). The sample sizes from Ontario public health units ranged from 164 (Elgin County) to 3,262 (Toronto). Residence was missing in just 30 (0.1%) individuals.

3.2.1 Characteristics of Area-level Variables

The mean income inequality across all 37 Ontario public health units, as measured by the Gini coefficient, was 0.37 with a standard deviation 0.018, and ranged from 0.34 to 0.44. The median area household income (Canadian Dollars) ranged from \$33,371 to \$63,407. Figure 3.1 shows that the Gini coefficient was moderately negatively correlated with median area income (Pearson's correlation coefficient, -0.47; 95% CI, -0.17 to –0.69). The Pearson's correlation coefficient was used because the Gini coefficients and median area incomes were roughly normal distribution.

Figure3.1 Income inequality by median area income for the 37 Ontario public health units



3.2.2 Self-reported Health Status (SRH), and its association with individual-level variables.

Of 30,939 people aged 25 or over, 30 individuals for whom residential status was missing were excluded from the analysis; 89 people of unknown marital status had a percentage 14.6% of self-rated poor/fair health which was not very different from that of people with complete data. These people were also excluded. Thus 30,820 people remained in the analysis for SRH. Table 3.2 shows the unweighted OHS sample characteristics and the percentage of subjects reporting fair or poor health for each category.

Overall, 12.8% of individuals reported their health as being either fair [n = 2,903; 9.4%] or poor [n = 1,052; 3.4%], whereas 87.2% reported their health as being excellent [n = 7,283; 23.6%], very good [n = 11,625; 37.6%], or good [n = 8,046; 26.0%]. Perceived poor health was associated with being unmarried, smoking, having low individual income or low educational attainment, and taking irregular exercise. Females were more likely to report their health as being fair or poor as compared with males. The percentage of people reporting poor/fair health increased with increasing age. People living in poor areas or areas with higher income inequality were more likely to report their health as being fair or poor than those living in rich areas or areas with lower income inequality, respectively.

Table 3.2 Prevalence (%) of poor/fair self-rated health status according to various risk factors, Ontario Health Survey 1996-97

	No.	Fair/poor	%
Overall	30820	3942	12.80
Individual-level Variables			
Age (years)			
25-39	11367	690	6.07
40-64	12843	1746	13.59
65+	6610	1506	22.78
Sex			
Male	14167	1702	12.01
Female	16653	2240	13.45
Income			
Low	3364	924	27.47
Middle	15686	1820	11.60
High	4091	215	5.26
Unknown	7679	983	12.80
Regular exercise			
Yes	22902	2057	8.98
No	7172	1614	22.50
Unknown	746	271	36.33
Marital status			
Married/common-law/partner	19255	2032	10.55
Single/widowed/separated/divorced	11565	1910	16.52
Smoking status			
Nonsmoker	12817	1352	10.55
Smoker	17895	2560	14.31
Unknown	108	30	27.78
Educational attainment			
<= Secondary	12939	2304	17.81
Post-secondary	17462	1539	8.81
Unknown	419	99	23.63
Area-level Variables			
Gini			
Low inequality	9896	1080	10.91
Medium inequality	8287	1143	13.79
High inequality	12637	1719	13.60
Median household income ($)			
Low	5373	813	15.13
Medium	11121	1504	13.52
High	14326	1625	11.34

3.2.3 The Health Utility Index (HUI), and its association with individual-level variables.

In addition to the 30 individuals with missing data on residence and 89 people with missing data on marital status, there were missing data for the HUI in 197 individuals (0.6%). These 316 people were excluded from the analysis. Thus 30,623 people remained in the analysis for HUI. Overall, 30.5% (n = 9,356) individuals had a score 1 on the HUI, which represented their health as being perfect. Table 3.3 summarizes the characteristics of the respondents (unweighted sample) and the percentage scoring <1 on the HUI for each variable.

Table 3.3 Prevalence (%) of people scoring < 1 on the HUI according to various risk factors, Ontario Health Survey 1996-97

	No.	HUI < 1	%
Overall	30623	21267	69.45
Individual-level variables			
Age (years)			
25-39	11328	5553	49.02
40-64	12771	9780	76.58
65+	6524	5934	90.96
Sex			
Male	14076	9242	65.66
Female	16547	12025	72.67
Individual income			
Low	3335	2634	78.98
Medium	15626	10683	68.37
High	4081	2581	63.24
Unknown	7581	5369	70.82
Regular exercise			
Yes	22829	15264	66.86
No	7089	5401	76.19
Unknown	705	602	85.39
Marital status			
Married/common-law/partner	19161	12880	67.22
Single/widowed/separated/divorced	11462	8387	73.17
Smoking status			
Nonsmoker	12723	8465	66.53
Smoker	17801	12733	71.53
Unknown	99	69	69.70
Educational attainment			
<= Secondary	12834	9615	74.92
Post-secondary	17387	11330	65.16
Unknown	402	322	80.10
Area-level variables			
Gini			
Low inequality	9834	6648	67.60
Medium inequality	8233	5844	70.98
High inequality	12556	8775	69.89
Median household income (S)			
Low	5333	3890	72.94
Medium	11053	7727	69.91
High	14237	9650	67.78

Consistent with the results for self-reported fair or poor health, most individual characteristics were associated with scores on the HUI. Being unmarried, smoking, having low individual income or low education attainment and taking infrequent exercise were positively associated with poor health. Females reported poorer health than males. The percentage of people scoring <1 on the HUI increased with increasing age. Finally, people living in areas with high income inequality and in poor areas were more likely to be in poor health as compared with those living in areas with low income inequality and in rich areas, respectively.

3.2.4 Missing Data

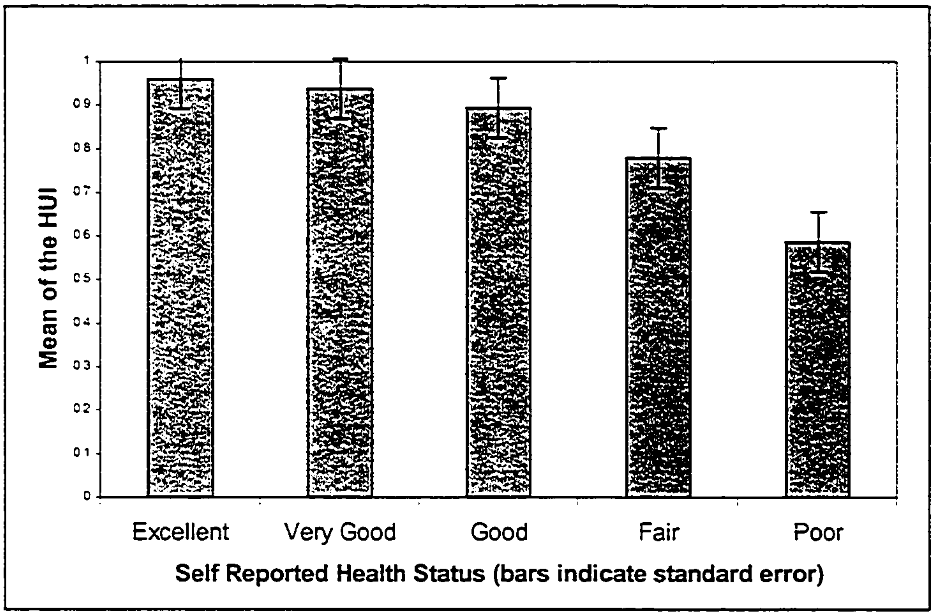
Of the 30,820 respondents used in the analysis for SRH, 24.9% did not report the amount of their income. The percentage of these people reporting poor or fair health was 12.8%. Age, sex, and education level were related to income non-response. Females (54.9%), middle-age people (42.2%), and people with low or high education level (24.9% and 33.1%) were more likely not to report their income. Physical activity, education attainment, and smoking were missing in 746, 419, and 108 individuals, respectively. We created a dummy variable to keep these people in the multilevel analysis because income was missing in as high as 24.9% of the study sample, and people missing data for other variables had higher percentages of poor health than did people with complete data; the reason was that middle-aged and elderly people were more likely not to report their physical activity, educational attainment, and smoking status, and elderly people generally have poorer health than young people.

3.3 Bivariate Correlations

3.3.1 Relationship between Self-reported Health Status and the HUI

Figure 3.1 shows the relationship between self-reported health status and the HUI. People reporting their health as being excellent, very good, good, fair, or poor had mean HUI 0.96, 0.94, 0.90, 0.78, and 0.59, with standard deviation 0.06, 0.08, 0.12, 0.19, and 0.24, respectively. As expected, the poorer the people reported their health, the lower the HUI.

Figure 3.2 Average HUI score by self-reported health status, OHS 1996-97



3.3.2 Bivariate Correlation between Income Inequality and Health

Table 3.4 presents the age-standardized percentage of fair/poor health and people scoring < 1 on the HUI for each Ontario Public Health Unit. Analyses are presented for the two dependent variables adjusted for age (25-39,40-49,50-59, 60-69, and 70+) using direct standardization (the total sample in the study was used as the standard). Toronto had the largest Gini coefficient (0.44) but relatively low age-standardized percentages of self-rated fair/poor health (12.8%) and people scoring <1 on the HUI (68.6%) compared with the other 36 public health units.

Table 3.4 Income inequality and age-standardized percent of fair/poor health and less than perfect health (HUI < 1) in 37 Ontario Public Health Units.

Public Health Unit	Gini	Fair/poor (%)	HUI<1 (%)
Durham Region	0.3375	10.58	69.85
Peel Region	0.3443	10.75	65.76
Perth County	0.3515	11.77	69.45
Oxford County	0.3531	13.11	66.08
Halton Region	0.3548	8.16	68.19
Leeds, Grenville and Lanark	0.3576	13.02	70.09
York Region	0.3582	10.15	66.83
Haldimand-Norfolk Region	0.3584	14.33	69.32
Wellington-Dufferin -Guelph	0.3590	10.78	69.22
Elgin-St. Thomas	0.3591	12.92	71.90
Renfrew County	0.3605	15.14	69.58
Simcoe County	0.3616	12.12	67.72
Huron County	0.3618	11.40	68.85
Thunder Bay	0.3676	16.12	72.89
Haliburton, Kawartha, Pine Ridge District	0.3678	13.39	70.64
Northwestern	0.3688	15.13	73.60
Muskoka-Parry Sound	0.3695	12.76	68.78
Brant County	0.3705	13.04	69.16
Hasting & Prince Edward Counties	0.3713	14.75	71.19
Chatham-Kent	0.3717	13.72	69.87
Lambton	0.3721	13.60	67.42
Grey-Bruce	0.3750	11.97	69.96
Eastern Ontario	0.3751	12.79	70.56
Waterloo Region	0.3752	10.86	68.83
Niagara Region	0.3770	12.52	67.26
Peterborough County-City	0.3777	14.26	70.66
Porcupine	0.3778	15.15	71.57
Ottawa-Carleton Region	0.3806	11.10	69.58
Kingston, Frontenac and Lennox & Addington	0.3814	14.98	71.38
Windsor-Essex	0.3869	15.68	71.05
Middlesex-London	0.3894	10.59	70.21
North Bay	0.3900	16.79	75.03
Sudbury	0.3909	17.87	71.63
Hamilton-Wentworth	0.3925	12.65	71.35
Algoma	0.3947	16.38	69.65
Timiskaming	0.4037	16.09	73.85
Metro Toronto	0.4385	12.82	68.64

The ecological-level correlation between the Gini coefficient and the age-standardized percentage of residents in fair or poor health was 0.42 (95% CI, 0.11 to 0.65). Figure 3.2 shows the scatter plot for the crude (i.e., unadjusted for individual income or other covariates except for age) bivariate relationship between age-standardized percentage of fair/poor health status and income inequality across the 37 public health units, and suggests a moderate degree of direct association (r = 0.42, p = 0.01). The correlation coefficient increased to 0.55 (95% CI, 0.27 to 0.74) if Toronto (To on scatter plot) was excluded.

Figure 3.3 Age-standardized percentage of self-rated poor/fair by income inequality for the 37 Ontario public health units

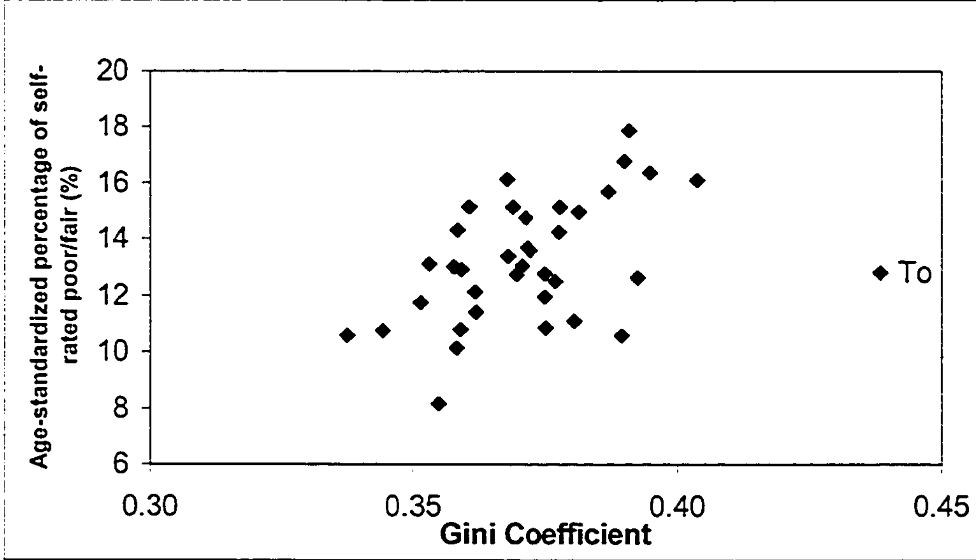
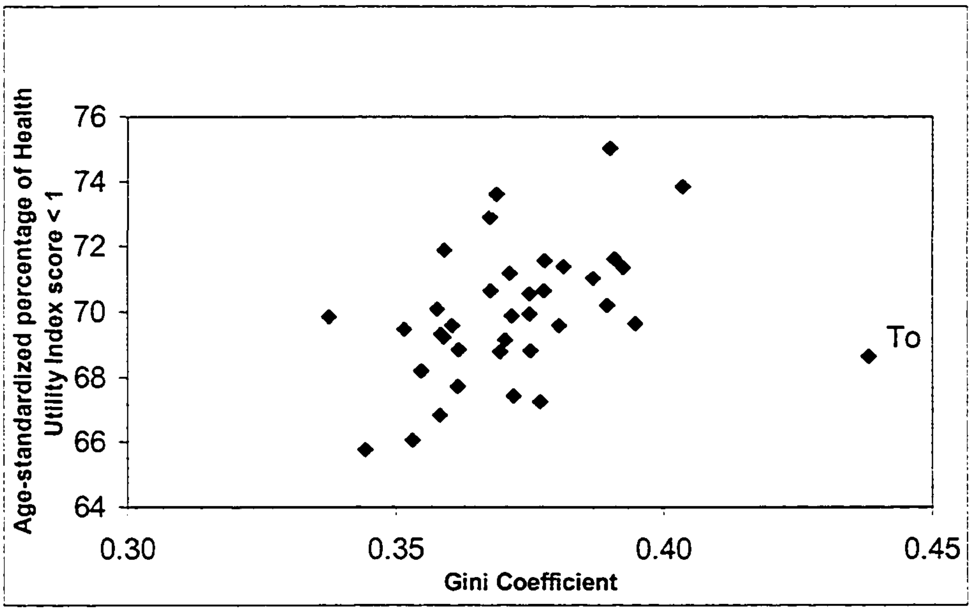


Figure 3.3 shows the relationship between age-standardized percentage of people scoring <1 on the HUI and the Gini coefficient, and indicates a modest but significant association between income inequality and people scoring <1 on the HUI (Pearson correlation coefficient r = 0.36, 95% CI, 0.04 to 0.61). The

correlation coefficient increased to 0.54 (95% CI, 0.26 to 0.74) if Toronto was omitted.

Figure 3.4 Age-standardized percentage of the Health Utility Index score <1 by income inequality for the 37 Ontario public health units



3.4 Multilevel Logistic Regression

3.4.1 Results for SRH from multilevel logistic models

Table 3.5 presents the results from the multilevel logistic regression models, including fixed and random components. The variance presented in the last row of the table is the variance of the coefficients for the intercepts in the multilevel model (τ_{00}^2 on page 9). Note that since the variance is estimated from the sample data, it has a standard error. When using a Wald test to test its difference from zero, it is appropriate to use one-sided test (critical value of Z= 1.65).

Table 3.5 Odds ratios for fair or poor self-rated health: multilevel multiple logistic regression analysis.

	Empty Model	Model 1		Model 2	
		OR	95% CI	OR	95% CI
Fixed effects					
Age (years)					
25-39		1.00		1.00	
40-64		2.19	1.99-2.42	2.20	2.00-2.42
65+		3.44	3.09-3.82	3.44	3.10-3.83
Sex					
Male		1.00		1.00	
Female		1.07	0.99-1.16	1.07	0.99-1.15
Income					
Low		3.92	3.33-4.61	3.91	3.32-4.60
Medium		1.62	1.41-1.87	1.62	1.41-1.87
High		1.00		1.00	
Unknown		1.36	1.17-1.58	1.36	1.17-1.58
Regular exercise					
Yes		1.00		1.00	
No		2.32	2.14-2.51	2.32	2.15-2.51
Unknown		4.75	4.09-5.53	4.77	4.10-5.55
Marital status					
Married/common-law/partner		1.00		1.00	
Single/widowed/separated/divorced		1.35	1.25-1.47	1.35	1.24-1.46
Smoking status					
Nonsmoker		1.00		1.00	
Smoker		1.37	1.27-1.48	1.37	1.27-1.48
Unknown		1.69	1.07-2.65	1.69	1.07-2.65
Educational attainment					
<= Secondary		1.43	1.32-1.55	1.43	1.32-1.55
Post-secondary		1.00		1.00	
Unknown		1.37	1.06-1.76	1.36	1.06-1.76
Gini					
Low				1.00	
Medium				1.17	1.02-1.34
High				1.25	1.10-1.42
Random effects: variance (standard error) Level 2	0.038(0.012)	0.016(0.008)		0.009(0.006)	

Model 1: adjustment for all 7 individual-level variables
Model 2: adjustment for all 7 individual-level variables and the Gini coefficient

For the random effects, the level-2 variance (0.038) in the empty model was significant, suggesting differences in SRH between public health units. However, this may well be an artefact of not taking into account key compositional characteristics. This is corrected in Model 1, in which the level-2 variation was estimated after adjusting for individual compositional characteristics. After allowing for individual characteristics, a Wald test showed that significant variation remained even though the amount of variation between public health units had fallen from 0.038 (Empty Model) to 0.016 (Model 1). In other words, the observed variations in SRH cannot be accounted by the individual factors included alone. At this step, we can see that 58% [(0.038-0.016)/0.038] of the variance between areas can be explained by the individual factors. The intra-class correlation coefficient was 0.01 [0.038/(0.038+3.29)], indicating that the individuals within the same area were only slightly more alike than individuals coming from different areas.

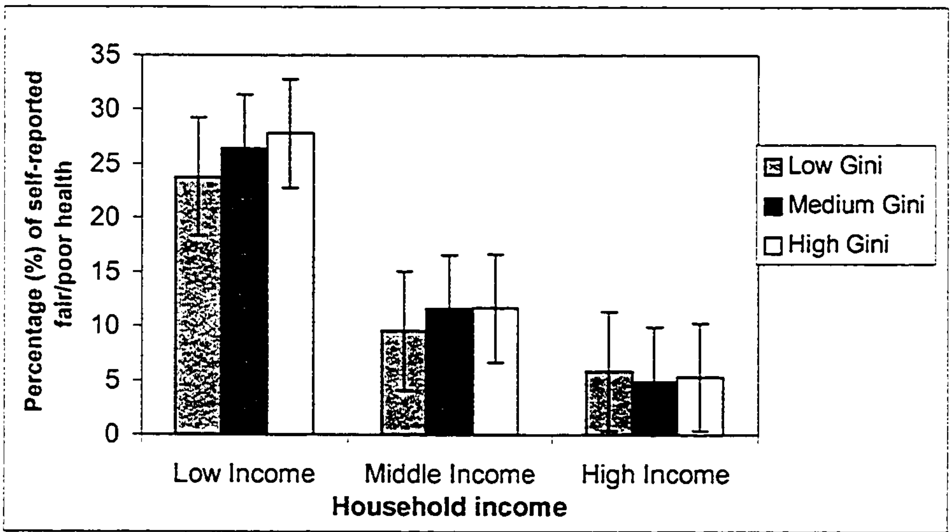
In Model 2, we added the Gini coefficient to model 1. In the fixed component, as expected, poor persons were 3.9 times more likely to perceive their health as fair or poor compared with rich persons. All the individual compositional factors were significantly associated with poor health, except for sex. Although women reported being in fair or poor health slightly more than men, this difference was not significant in the fully adjusted model (odds ratio for female 1.07, 95% CI: 0.99 to 1.15).

There was a gradient in the odds ratio for fair or poor health across levels of income inequalities. Compared with respondents living in areas with the lowest income inequality (category 1), those living in areas with the highest income inequality (category 3) were 1.25 times more likely to report fair/poor health.

Cross-level Effect Modification

Figure 3.4 explores whether associations of area income inequality with fair or poor health differ by individual-level income (i.e. was there an interaction between individual-level income and area income inequality?). It serves as an initial exploratory investigation of whether inequality effects differ by individual income, before examining the more complex multilevel models.

Figure 3.5 Self-reported fair or poor health by individual income, and income inequality, OHS 1996-97



There appears to be an interaction: poor persons living in areas in the lowest income inequality category had a lower percentage (23.8%) of fair/poor health than poor persons residing in areas with the highest income inequality (27.8%). The same pattern was evident for middle-income persons, although the differences were smaller, while there was no influence of Gini scores for rich people.

When we examined potential cross-level effect modification of the Gini effect by age and sex in the multilevel model, no meaningful effect modifications were found. There was weak apparent effect modification by individual income, although it did not reach the traditional level of statistical significance (p for trend = 0.13).

Table 3.6 shows the results from multilevel model (model 2) in which we added an interaction term of Gini with individual-level income. Although most did not reach the statistical significance, the multilevel model showed stronger effects of income inequality on health in individuals with lowest and middle incomes: the odds ratios for fair or poor health were 1.44 (95% CI: 1.08, 1.94) and 1.26 (95% CI: 0.94,1.69) respectively, when areas with the highest income inequality were compared with areas with the lowest income inequality.

Table 3.6 Self-rated fair or poor health by individual income; multilevel analysis (model 2) with interaction terms.

Income groups	Odds ratio (95% Confidence Interval) for fair or poor health	
	OR	95% CI
Low Income		
Low Gini	1.00	
Medium Gini	1.10	0.72-1.67
High Gini	1.44	1.08-1.94
Middle Income		
Low Gini	1.00	
Medium Gini	1.20	0.79-1.83
High Gini	1.26	0.94-1.69
High Income		
Low Gini	1.00	
Medium Gini	0.82	0.54-1.25
High Gini	0.98	0.73-1.32

Potential Confounder —Median Area Income

To detect the potential confounding effect of median area income, the results from multilevel models before and after adjusting for median area income are presented in Table 3.7, using self-rated health as the dependent variable.

The first column in Table 3.7 simply reproduces the odds ratio from model 2 in Table 3.5. The second column shows the effect of controlling for PHU-level median household income on self-rated health. The patterning was relatively marked for the Gini coefficient and, to a lesser degree for median area income. Including median area income reduced the odds ratio for area with medium and high income inequality by only 3.9% and 4.3% respectively, and the odds ratio for the medium income inequality (category 2) was no longer significant (95% CI, 0.97 to 1.30). It suggests that including median area income in the model had little effect on the point estimates of income inequality at the public health unit level.

Table 3.7 Odds ratios (95% confidence intervals) of income inequality, before and after adjusting for median area income

	Model 2		Model 3	
	OR	95%CI	OR	95%CI
Gini				
Low	1.00		1.00	
Medium	1.17	1.02-1.34	1.13	0.97-1.30
High	1.25	1.10-1.42	1.19	1.10-1.30
Median Area Income				
Low			1.11	0.96-1.20
Medium			1.04	0.91-1.20
High			1.00	

Model 2: adjustment for all 7 individual-level variables and the Gini coefficient
Model 3: adjustment for all 7 individual-level variables, the Gini coefficient, and median area income

3.4.2 Results for HUI < 1 from the Multilevel Logistic Model

The odds ratios for scoring < 1 on the HUI in the multilevel logistic regression models are presented in Table 3.8.

Table 3.8 Results for less than perfect health (HUI < 1): multilevel logistic regression models

	Empty Model	Model 1		Model 2	
Fixed effects		OR	95%CI	OR	95%CI
Age (years)					
25-39		1.00		1.00	
40-64		3.32	3.14-3.50	3.32	3.14-3.51
65+		10.17	9.18-11.26	10.15	9.16-11.23
Sex					
Male		1.00		1.00	
Female		1.37	1.30-1.45	1.37	1.30-1.45
Income					
Low		1.31	1.17-1.47	1.31	1.17-1.47
Middle		1.01	0.93-1.08	1.00	0.93-1.08
High		1.00		1.00	
Unknown		0.94	0.87-1.03	0.94	0.87-1.03
Regular exercise					
Yes		1.00		1.00	
No		1.27	1.19-1.36	1.27	1.19-1.36
Unknown		1.85	1.53-2.25	1.85	1.53-2.25
Marital status					
Married/common-law/partner		1.00		1.00	
Single/widowed/separated/divorced		1.21	1.14-1.28	1.20	1.13-1.28
Smoking status					
Nonsmoker		1.00		1.00	
Smoker		1.33	1.26-1.40	1.33	1.26-1.40
Educational attainment					
<= Secondary		1.03	0.97-1.09	1.03	0.97-1.09
Post-secondary		1.00		1.00	
Unknown		1.38	1.08-1.77	1.38	1.08-1.76
Gini					
Low				1.00	
Medium				1.10	1.00-1.22
High				1.14	1.04-1.25
Random effects: variance (standard error)					
Level 2	0.016 (0.005)	0.006(0.003)		0.004(0.003)	

Model 1: adjustment for all 7 individual-level variables

Model 2: adjustment for all 7 individual-level variables and the Gini coefficient

In the random parts, there was a small but statistically significant level-2 variation (variance = 0.016) between areas in the empty model, suggesting differences in poor health between public health units. After allowing for individual characteristics, the amount of variation between public health units fell to 0.006 (Model 1), but was still significant. In other words, the variation between areas cannot be fully explained by individual factors. At this step, we can see that 62.5% [(0.016-0.006)/0.016] of variance between areas can be explained by a range of individual-level variables. The intra-class correlation coefficient was 0.005 [0.016/(0.016+3.29)], suggesting that individuals within areas are not much more similar to one another than individuals from different areas.

For the fixed parts in Model 2, the significant variables were similar to the model for self-reported health status, with the exceptions that educational attainment was not significant and sex turned out to be significant.

Low income persons had an odds ratio of 1.31 (95% CI, 1.17 to 1.47) for scoring < 1 on the HUI, compared with high income persons. Model 2 shows that individuals living in areas with high income inequality had an odds ratio of 1.14 for less than perfect health (95% CI, 1.04 to 1.25), compared with individuals in the areas with lowest income inequality.

We found no significant effect modification by age, sex, or individual income. The results for the HUI were consistent with those for self-reported health status, although the odds ratios for HUI < 1 were smaller.

Potential Confounder — Median Area Income

Table 3.9 shows the results for people scoring < 1 on the HUI from multilevel models, before and after adjusting for median area income. Similar to the results for self-reported fair/poor health, we can see a marked pattern for income inequality, but no effect for median area income on HUI < 1.

Including area median income reduced the odds ratio for income inequality by only 1.1%, but the confidence interval for the odds ratio in medium income inequality (category 2) turned to be wider (95% CI, 0.98 to 1.21). As noted earlier, the power to test the significance for the income inequality was reduced by including area median income in the model (including median area income reduced the precision of the OR estimate for Gini).

Table 3.9 Odds ratios (95% confidence intervals) of income inequality for HUI < 1, before and after adjusting for median area income

	Model 2		Model 3	
	OR	95%CI	OR	95%CI
Gini				
Low	1.00		1.00	
Medium	1.10	1.0-1.22	1.09	0.98-1.21
High	1.14	1.04-1.25	1.13	1.02-1.25
Median Area Income				
Low			1.02	0.92-1.13
Medium			1.04	0.94-1.15
High			1.00	

Model 2: adjustment for all 7 individual-level variables and the Gini coefficient
Model 3: adjustment for all 7 individual-level variables, the Gini coefficient, and median area income

3.4.3 Results for HUI<0.947 (50th percentile of HUI) from the Multilevel Logistic Model

Table 3.10 presents the odds ratio for HUI < 0.947 (50th percentile of the HUI) from the multilevel logistic models. The association between income inequality and health still held. The odds ratio for income inequality in the highest category was 1.15 (95% CI, 1.05 to 1.26).

Table 3.10 Odds ratios for HUI<0.947 (50th percentile) in the multilevel logistic regression models

	Empty Model	Model1		Model2	
		OR	95% CI	OR	95% CI
Fixed effects					
Age (years)					
25-39		1.00		1.00	
40-64		1.77	1.67-1.88	1.77	1.67-1.88
65+		2.90	2.69-3.11	2.89	2.69-3.11
Sex					
Male		1.00		1.00	
Female		1.15	1.09-1.21	1.15	1.09-1.21
Income					
Low		2.45	2.20-2.74	2.45	2.19-2.73
Middle		1.35	1.25-1.46	1.35	1.24-1.46
High		1.00		1.00	
Unknown		1.11	1.01-1.21	1.11	1.01-1.21
Regular exercise					
Yes		1.00		1.00	
No		1.63	1.53-1.73	1.63	1.53-1.73
Unknown		3.88	3.36-4.49	3.88	3.36-4.49
Marital status					
Married/common-law/partner		1.00		1.00	
Single/widowed/separated/divorced		1.41	1.33-1.49	1.41	1.33-1.49
Unknown		0.93	0.54-1.61	0.93	0.54-1.61
Smoking status					
Nonsmoker		1.00		1.00	
Smoker		1.34	1.28-1.42	1.34	1.28-1.42
Educational attainment					
<= Secondary		1.12	1.06-1.18	1.12	1.07-1.18
Post-secondary		1.00		1.00	
Unknown		1.34	1.09-1.63	1.33	1.09-1.63
Gini					
Low				1.00	
Medium				1.13	1.03-1.25
High				1.15	1.05-1.26
Random effects: variance (standard error)					
Level 2	0.021(0.007)	0.008(0.004)		0.005(0.003)	

Table 3.11 shows the results for the HUI < 0.947 from multilevel models, before and after adjustment for median area income. Adjustment for median area income had no effect on the association between income inequality and health.

Table 3.11 Odds ratios of income inequality, before and after adjusting for median area income (using 50th percentile as cut-point for HUI)

	Model 2		Model 3	
	OR	95%CI	OR	95%CI
Gini				
Low	1.00		1.00	
Medium	1.13	1.03-1.25	1.13	1.01-1.25
High	1.15	1.05-1.26	1.15	1.03-1.27
Median Area Income				
Low			1.04	0.89-1.10
Medium			1.04	0.94-1.15
High			1.00	

Model 2: adjustment for 7 individual variables and Gini
Model 3: adjustment for 7 individual variables, Gini, and median area income

3.5 Comparing the Results of Standard Contextual Analysis with Multilevel Analysis

Table 3.12 presents the results for self-reported fair or poor health from multilevel analysis and from standard contextual analysis, respectively.

Table 3.12 Comparing the results for fair or poor health from multilevel model with standard contextual model

	Results from Multilevel analysis		Results from standard contextual analysis	
	OR	95%CI	OR	95%CI
Age (years)				
25-39	1.00		1.00	
40-64	2.20	2.00-2.42	2.20	2.00-2.42
65+	3.44	3.10-3.83	3.45	3.10-3.83
Sex				
Male	1.00		1.00	
Female	1.07	0.99-1.15	1.07	0.99-1.16
Income				
Low	3.91	3.32-4.60	3.94	3.35- 4.64
Middle	1.62	1.41-1.87	1.63	1.42-1.88
High	1.00		1.00	
Unknown	1.36	1.17-1.58	1.37	1.18-1.59
Regular exercise				
Yes	1.00		1.00	
No	2.32	2.15-2.51	2.32	2.14- 2.51
Unknown	4.77	4.10-5.55	4.75	4.08- 5.52
Marital status				
Married/common-law/partner	1.00		1.00	
Single/widowed/separated/divorced	1.35	1.24-1.46	1.34	1.24-1.46
Smoking status				
Nonsmoker	1.00		1.00	
Smoker	1.37	1.27-1.48	1.38	1.28- 1.49
Unknown	1.69	1.07-2.65	1.68	1.07- 2.64
Educational attainment				
<= Secondary	1.43	1.32-1.55	1.44	1.34-1.56
Post-secondary	1.00		1.00	
Unknown	1.36	1.06-1.76	1.36	1.05-1.76
Gini				
<= 0.36184 (low)	1.00		1.00	
0.36184-0.37766 (middle)	1.17	1.02-1.34	1.16	1.04-1.29
>= 0.37766	1.25	1.10-1.42	1.20	1.10-1.31

As expected, the point estimates for the Gini coefficient and other covariates were very close for the two methods. Furthermore, the 95% confidence interval for each point estimate was also almost identical in multilevel analysis and in the standard contextual method. The odds ratios for income inequality changed more than did those for individual-level variables.

3.6 Comparing Results of Multilevel Analysis Using the SAS Glimmix macro with MLwiN

Table 3.13 shows the results for SRH from fully adjusted multilevel models using the SAS Glimmix macro and MLwiN. The results from multilevel analysis using SAS Glimmix macro are almost identical to those from MLwiN for both fixed effects and random effects.

Table 3.13 Odds ratios (95% confidence intervals) for SRH from multilevel analysis using SAS and using MLwiN

	Glimmix		**MLwiN**	
	OR	95% CI	OR	95% CI
Fixed effects				
Age (years)				
25-39	1.00		1.00	
40-64	2.20	1.99-2.42	2.20	2.00-2.42
65+	3.44	3.09-3.82	3.44	3.10-3.83
Sex				
Male	1.00		1.00	
Female	1.07	0.99-1.15	1.07	0.99-1.15
Income				
Low	3.91	3.32-4.60	3.91	3.32-4.60
Middle	1.62	1.41-1.86	1.62	1.41-1.87
High	1.00		1.00	
Unknown	1.36	1.17-1.58	1.36	1.17-1.58
Regular excise				
Yes	1.00		1.00	
No	2.32	2.14-2.51	2.32	2.15-2.51
Unknown	4.76	4.09-5.54	4.77	4.10-5.55
Marital status				
Married/common-law/partner	1.00		1.00	
Single/widowed/separated/divorced	1.35	1.24-1.46	1.35	1.24-1.46
Smoking status				
Nonsmoker	1.00		1.00	
Smoker	1.37	1.27-1.48	1.37	1.27-1.48
Unknown	1.68	1.07-2.64	1.69	1.07-2.65
Educational attainment				
<= Secondary	1.43	1.32-1.55	1.43	1.32-1.55
Post-secondary	1.00		1.00	
Unknown	1.36	1.05-1.76	1.36	1.06-1.76
Gini				
Low	1.00		1.00	
Medium	1.17	1.02-1.34	1.17	1.02-1.34
High	1.25	1.10-1.42	1.25	1.10-1.42
Random effects: variance (standard error)				
Level 2	0.009(0.006)		0.009(0.006)	

Chapter 4 Discussion

4.1 Summary of Findings

In this cross-sectional analysis of an Ontario representative sample we have shown that income inequality at public health unit level has a significant association with an individual's self-reported poor health (SRH or HUI) even after controlling for a range of individual-level factors and median area income. Our study suggests that important differences exist between public health units and that an individual's health depends not only on individual characteristics but on area income inequality as well, although the effect of income inequality was modest compared with that of individual-level income.

4.2 Interpretation of Findings in Light of Other Studies and Theory

4.2.1 Justification for Our Multilevel Study

Only a handful of publications in the 1980s and early 1990s suggested that "area" may be important to health (Carstairs et al., 1989; Diehr et al., 1993), but interest has increased sharply in recent years. Documentation of area effects, as well as elucidation of the mechanisms through which they are mediated, have implications for disease prevention and health policy.

Although ecologic studies may be useful to document and monitor inequalities in health, they cannot directly determine whether differences across areas are due to characteristics of the areas themselves or to differences between the types of individuals living in different areas. They cannot evaluate the role of individual-level factors as confounders, or modifiers of the area-level variables.

Contextual analysis and multilevel analysis can simultaneously include both individual- and area-level factors in the model, but they should be used in different situations (Diez-Roux, 2000). For example, if the variation between areas is estimated as 0, a contextual model including relevant area- and individual-level variables may be an adequate and simpler formulation. However, if variation between areas is indeed present, multilevel model is a more appropriate option.

Our results showed that there was small but significant variation in self-reported fair/poor health (SRH) and less than perfect health (HUI) among 37 Ontario public health units, even after controlling for a range of individual factors, so multilevel analysis is called for. Multilevel logistic models allow for between-area variability to be explained simultaneously by individual- and area-level factors. Using multilevel analysis is one of the strengths of our study.

4.2.2 Comparing Results from Different Approaches and Software

When comparing the results for fair or poor health from multilevel model with a standard contextual model, we found that both point estimates and corresponding 95% confidence intervals for each variable were very close between the two methods, although the odds ratios for income inequality differed more than did those for individual-level variables. The main reason for the small differences could be that the between-public health unit variation for the two outcomes was rather small (0.038 for fair or poor health and 0.016 for less than perfect health), although they reached the traditional level of statistical significance, which resulted in very small intra-class correlations. The big cluster sizes (from 164 to 3262 people) may also be an important factor. The relatively small number of areas (37 public health units) may explain why the point estimates of area-level variable (e.g., the Gini) shifted more than individual-level variables.

In addition, we found that the results from multilevel analysis using the SAS Glimmix macro were almost identical to those from MLwiN for both fixed effects and random effects. It has been reported that the estimate from the SAS Glimmix macro is particularly close to the estimate from MLwiN's PQL-1. The Glimmix macro is based on Wolfinger & O'Connell's (1993) pseudo-likelihood (PL), which is the same as Breslow & Clayton's (1993) PQL-1 except that PL explicitly estimates the extra-dispersion parameter Φ, while PQL-1 sets Φ to one. However, this Glimmix macro can produce biased results if there are only a few subjects within each area (Ramon et al., 1996). In our case, there were sufficient subjects within each public health units (from 164 to 3262 people). Hence, the results from SAS Glimmix macro would be expected to be close to those from MLwiN.

4.2.2 Relationship between Self-rated Fair/Poor and the Health Utility Index

In our study, the first health indicator is self-reported fair/poor health, a widely used indicator that is based on respondents' own assessment of their health. However, the opinion has been expressed that self-rated data are too subjective, and therefore not as valid a measure of health status as standardized mortality rates or diagnoses obtained from health examinations would be.

The second indicator is the McMaster Health Utility Index (HUI) score, which is based on functional status assessed in eight domains (Torrance et al., 1992). It may be considered a more reliable health measure because of the explicit inclusion of the eight health dimensions. The HUI was checked for its correspondence with self-reported fair/poor health, to test whether they lead to different results. Our results clearly indicated that the poorer the people reported their health, the lower the HUI. Moreover, in the fully adjusted multilevel model, income inequality appeared to exhibit a significant adverse effect on both health indicators, although its effect on relatively poor health (either HUI<1 or <0.947) was smaller. The choice of cut-points to categorize these health indicators may partly account for the difference between the results for the two health outcomes. Also, it might be that self-reported health overestimates the level of health inequalities. For example, higher income individuals might report better health given the same HUI score because of greater ability to mobilize coping resources. However, a review of 27 studies has shown that this simple measure of self-rated health (SRH) has strong predictive validity for mortality, independent of other physiological, behavioral, and psychosocial risk factors (Idler et al., 1997). Furthermore, it has been shown in longitudinal studies that self-rated health predicts the onset of disability (Ferraro et al., 1997; Idler et al., 1995).

4.2.3 Association between Individual-level Factors and Health

Our results from multilevel models indicated that about 60% of the between-area variance in self-reported fair/poor health and proportion scoring < 1 on the HUI could be explained by a range of individual factors, including individual income. It is clear that the individual characteristics play a dominant role in health. The probability of reporting self-reported fair/poor health decreased with increasing individual income, consistent with the 'absolute-income' hypothesis (Davey-Smith et al., 1996; Ecob & Davey-Smith; 1999). Many other studies have demonstrated a strong inverse relationship between individual income and health. For example, Wilkins et al. (1989) demonstrated an association between income and mortality by looking at deaths occurring to residents of urban centres in Canada during the period 1971-1986. Using a representative sample of the Manitoba population, Mustard et al. (1997) reported that mortality was inversely related to both income and education.

We found that Toronto had the largest Gini coefficient (0.44) but relatively low age-standardized percentage of self-rated fair/poor health (12.8%) and less than perfect health (68.6%), compared with the other 36 public health units. There are three possible reasons for Toronto's good health.

1) The proportion of immigrants within the population of Ontario has been increasing (Public Health Research, Education & Development Program, 2000). Between 1991 and 1996, the proportion of the population that was immigrants rose from 24% to 26%. This increase was concentrated in Toronto, where the proportion of immigrants rose from 42% in 1991 to 48% in 1996. Thus, in 1996, almost one half of the non-institutional population of Toronto reported themselves as being immigrants to Canada. Immigrants are selected to be healthy.

2) Toronto has proportionately more persons aged 30-34 years old then the rest of the province. These people may be correspondingly healthy, since these people are at the young end of the age range considered in this study. Approximately 10% of the population of Toronto is in this narrow age band. The degree to which this represents immigration from abroad or migration of young Canadians to the city is unknown.

3) The lowest rates of smoking and highest rates of smoke-free homes occurred in Toronto, and smoking is one of the strongest risk factors associated with health.

4.2.4 Association between Income Inequality and Individual Health

Our findings suggested a contextual effect of income inequality at the public health unit level on health after individual sociodemographic characteristics are controlled for, although the contextual effect was modest compared with that of individual-level income. Since the analysis used a multilevel approach, and took a range of individual-level factors into account, the association between income inequality and individual health is not likely to be the product of the ecological fallacy.

Previous studies examining a contextual effect of income inequality on individual health outcomes have reached conflicting conclusions. Some studies have found that an adverse effect of income inequality on self-reported health persisted after adjustment for individual income. For instance, Kennedy et al (1998) found that high income inequality significantly increased the odds of fair or poor health among those adults already at two to threefold greater risk because of low individual income. However, Fiscella and Franks (1997) reported that individual income could account entirely for the mortality effects attributed to income inequality. They found that the ecological effect of income inequality at the level of community disappeared after including individual income in the model. They suggested that income inequality was capturing the compositional effect of individual income on health — that is, areas with more poor individuals have greater inequalities in income, producing a spurious association between income inequality and poor health, since being poor is associated with poor health.

A number of potential explanations may account for the differences between our findings and those of Fiscella and Franks. Firstly, our study used different health indicators such as self-reported health and the HUI; these self-reported variables may be more sensitive to income inequality. Secondly, they used a different level of aggregation (community), which might be too small to allow income distribution to exert an effect in terms of variations in income distribution. Another reason for the different findings may be in measurement of income inequality. In Fiscella and Franks' study, the measures of income inequality were derived from the distribution of income based on their study sample, and were truncated at $25,000. This may have underestimated the degree of true inequality. A more appropriate measure of income inequality could be derived from census data. Finally, significant differences between Canada and the United States may prevent meaningful comparison.

4.2.5 Major Differences between Canada and the United States

When comparing the relation between mortality and income inequality in Canada with that in the United States, Ross and colleagues (2000) found that there was no significant association in Canada at either the provincial or metropolitan area level, whereas such associations were apparent in the United States. They argued that structural differences between the two countries could account for the difference in the relation of inequality to mortality. One plausible difference is the greater degree of economic segregation in large US cities. Such segregation can create a spatial mismatch between workers and jobs, and large inequalities in provision of public goods and services (for example, schools, transportation, health care, policing, house, etc) because of concentrations of people with high social needs in municipalities with low tax bases. Another major difference is the way in which resources such as health care and high quality education are distributed. In the United States these resources tend to be distributed by the marketplace so their utilization tends to be associated with ability to pay; in Canada they are publicly funded and more universally available.

Contrary to Ross, we found that high income inequality was associated with poor health, independent of individual-level factors including individual income. The reason for the different results might be that we used a different level of geographic aggregation from that in Ross's study. It is not unreasonable to expect the association of income inequality with health to vary by unit of analysis. Also, the association might exist in some regional areas but not others.

On the other hand, income inequalities among families in Canada have been increasing in the last generation (Yalnizyan, 1998). For example, in 1973, 60% of families with children under 18 earned between $24,500 and $65,000 (in 1996 dollars). By 1996, that middle class shrunk: only 44% of such families made such income. Moreover, average earnings of the poorest 10% of families fell from $7,220 in 1973 (in 1996 dollars) to $1, 823 in 1996. That is because the number of families without any earners has grown dramatically over the last generation. In 1973 about two-thirds of the poorest families had at least some earnings. In 1996, three-quarters of the poorest families have no earner. Growing income gap may have implications in health.

4.2.6 Mechanisms for the Effect of Income Inequality on Health

Several mechanisms have been suggested.

Income inequality leads to under-investment in human capital. In the United States, Kaplan et al. (1996) reported that states with high income inequality (as measured by the proportion of total household income received by the less well-off 50%) spent a smaller proportion of their state budget on education and showed poorer educational outcomes. One reason why high income inequality translates into lower social spending is that in societies with rising inequalities, the interests of the rich people began to diverge from those of the typical family (Berkman & Kawachi, 2000). As Paul Krugman described: "A family at the 95th percentile pays a lot more in taxes than a family at the 50th, but it does not receive a correspondingly higher benefit from public services, such as education. The greater the income gap, the greater the disparity in interests. This translates, because of the clout of the elite, into a constant pressure for lower taxes and reduced public service" (Krugman, 1996).

Income disparities disrupt the social fabric and lead to disinvestments in "social capital". Social capital is commonly thought to be composed of trust, norms, and networks. Wilkinson (1996) offers several case studies of societies that at certain points in history underwent either a rapid compression of the income distribution or a rapid widening of income differentials. For instance, in wartime Britain, narrowing of income differentials was accompanied by a greater sense of solidarity and social cohesion as well as dramatic improvements in life expectancy. More recently, Kawachi and colleagues (1997a) have tested the association between income inequality and social cohesion at the ecological level. They demonstrated that citizens living in states characterized by high income disparities tend to be more mistrustful of each other ($r = 0.71$). These examples seem to support the notion that income inequality erodes social cohesion. Thus, high income inequalities lead to low levels of social support and cohesion.

The mechanisms linking social capital to health outcomes have yet to be elucidated. Some evidence suggests that socially isolated individuals are at increased risk for poor health outcomes because of their limited access to resources such as instrumental aid, information, and emotional support. The more challenging task is to identify the mechanisms by which social capital may exert a contextual effect on individual health, which may occur in several different ways. First, social capital may influence the health behaviors of neighborhood residents by a) promoting more rapid diffusion of health information, b) increasing the likelihood that healthy norms of behavior are adopted (e.g., physical activity), and c) exerting social control over deviant health-related behavior. Second, it may influence health by increasing access to local services and amenities. Evidence from criminology suggests that socially cohesive neighborhoods are more successful at uniting to ensure that budget cuts do not affect local services such as transportation, community health clinics, or recreational facilities (Sampson et al., 1997). Such local services may be directly relevant to health. Finally, social capital may influence the health of individuals via psychosocial processes, by providing psychological support and acting as the source of self-esteem and mutual respect (Wilkinson, 1996).

Disparities in income result in poor health through direct psychological pathways. A third pathway by which income inequality might produce poor health is through psychologically mediated effects of relative deprivation (Kawachi et al., 1994; Wilkinson 1996). Relative deprivation may result in psychosocial stress, which can affect health both directly and indirectly through its effects on health behavior. The direct effects are likely to centre on the physiological effects of chronic mental and emotional stress. The indirect effects include any stress-related smoking, drinking, eating "for comfort" etc. Because the psychosocial stress may result from low social position, this implies that income inequality is a cause of health problems among the poor. Stress and depression may also lead some individuals to aggressive behaviors that have negative effect. For example, motor vehicle accidents, violent crime, and substance abuse have all been suggested as pathways by which the mental condition of one individual may have serious external effects on the health of others. Consequently, the effects of income inequality may be manifested in the health of all members of a community, not just the poor.

Furthermore, psychosocial stress may increase susceptibility to disease, and a great deal of recent study has been directed at establishing the pathways through which repeated exposure to stress compromises the immune system. It is possible that people's psychological circumstance could seriously damage their health in the long term. Chronic anxiety, insecurity and low self-esteem appear to undermine mental and physical health. The power of psychosocial factors to affect health also makes biological sense. Stress response would affect the cardiovascular and immune systems. If the biological stress response is activated too often, it may cause multiple health problems. These include depression, increased susceptibility to infection, diabetes, high blood pressure, and stroke. Psychosocial and stress mechanisms have been studied in a variety of non-human primates, both in the wild and in captivity. In baboons, those of lower status in the troop have a higher level of the stress hormone cortisol. In monkeys there is also a social hierarchy in cardiovascular damage (Sapolsky and Mott, 1987). Wilkinson (1996) suggested that psychosocial pathways might exert a more powerful influence on health in the developed world than do pathways involving direct exposure to material hazards.

Each of these 3 main possible mechanisms might work simultaneously, and merits further investigation. Much work remains to be carried out in this area.

4.2.7 Potential Confounding Effect of Median Area Income on the Association

In this study, the Gini coefficient was moderately negatively correlated with median area income. The probable reason is that lower median area income may be due to larger proportions of poor people in some areas, which might lead to wider income gaps.

The effect of income inequality, although attenuated somewhat, did not change significantly when median area income was included in the model. The power to test income inequality mainly depends on how many areas we have and how many level-2 variables were included in the model. A small number of areas (37 public health units) and including more level-2 variables such as area median income in the model could reduce the power to achieve statistical significance for income inequality (Greenland, 1989).

Interestingly, Soobader and LeClere (1999) found that the effect of income inequality at the census tract level in the US was no longer significant when median area income was added to the inequality-mortality model, while at the county level, adjusting for median area income had no effect on the association. Similarly, aggregating at metropolitan area (MA) level in the US, Blakely and colleagues (2001) found little association of MA-level income inequality with fair/poor health when controlling further for average MA household income.

Soobader and LeClere (1999) suggested that in small area like census tracts the effect of inequality is predominantly through differences in individual social class positions and the absolute economic standing of the tracts. At higher levels of aggregation, inequality is through both the social and political sequelae of economic segregation and the socioeconomic differences between places and people. The sum total of these effects is then evident at high levels of aggregation. Our results for the effect of median area income on the association are consistent with those of the US studies aggregated at large area level.

4.2.8 Potential Effect Modification by Individual Income

Interactions between area characteristics and individual-level factors have been less commonly investigated. Development and testing of specific hypothesis regarding interactions may help enhance our understanding of the processes involved.

Although a few studies have investigated interactions between area income inequality and individual-level factors, results have not been fully consistent regarding the types of interactions present. Among multilevel studies, only two reported that both income inequality and individual income increase the risk of poor health. Kennedy et al (1998) found that high income inequality significantly increased the odds of fair or poor health among those adults already at two to threefold greater risk because of low individual income; however, high income inequality was not associated with adverse health among those in the top income bracket in that study (>S35000). Kahn et al (2000) found that high income inequality conferred an increased risk of poor mental and physical health, particularly among the poorest women.

In our study, similarly, there appeared to be a modest association of PHU-level income inequality with self-reported health only among those people with low and middle income, although the confidence intervals were wide. The finding of such an interaction may help to focus research on the specific mechanisms by which income inequality operates. One interpretation is that low- and middle-income people living in an area with high income inequality may feel relatively poorer in general: the association between income inequality and health may be primarily mediated through psychosocial pathways (direct physiological effects of chronic stress) and through behaviors such as smoking, drinking, and overeating (indirect effects of stress). Our results suggest the need for more concerted efforts to explore the combined effects of income inequality and individual income.

4.2.9 Association between Income Inequality and Health as an Artefact

Although a considerable body of literature has shown that high income inequalities are associated with poor health, this finding has generated a great deal of debate. Gravella (1998) argued that the association may be no more than a statistical artefact: for a given level of average income, the higher the income inequality of a society, the higher will be the proportion of people in poverty. If the relation of absolute mortality rates to income is curvilinear, then an increase in income will reduce the risk of mortality by a smaller amount at high incomes than at low incomes. However, Wolfson and colleagues (1999) assessed the extent to which observed associations at the population level between income inequality and mortality were statistical artefacts. They concluded that the observed associations in the United States at the state level between income inequality and mortality cannot be entirely or substantially explained as statistical artefacts of an underlying individual level relation between income and mortality. There remains an important association between income inequality and mortality at state level over and above anything that can be accounted for by any statistical artefact.

4.3 Other Issues Related to the Association

Several issues still remain to be solved.

4.3.1 At what level of geographic aggregation does income inequality affect health?

The size and definition of the relevant geographic area may vary according to the outcomes being studied and the processes through which the area effect is hypothesized to operate. Areas ranging from small to large with varying geographic definitions may be important for different mediating mechanisms or for different health outcomes.

It is not clear at what level of analysis the contextual effects of income inequality are best specified (for example, province, county, or neighborhood). Elucidation of this issue would call for the simultaneous analysis of data at multiple levels (province, county, municipality, census tract and individual). Pinpointing the level of aggregation at which income distribution affects health outcomes will provide important clues about the etiological mechanisms involved and clarify the options for policy interventions.

Different studies have been carried out at different levels of geographic aggregation — whole countries, states within countries, counties and census tracts. For instance, the association between income inequality and mortality has been found in ecologic studies at high levels of geographic aggregation such as cross-country comparisons and national studies. At the state level in the United States, strong positive association (r = 0.62) was found (Kaplan et al., 1996).

However, Soobader and LeClere found that the income inequality effect at the census tract level was no longer significant after including average area income. They concluded that average area income and individual socioeconomic status are the dominant correlates of perceived health status at the tract level. Their results suggest that the level of geographic aggregation influences the pathways through which income inequality is actualized into an individuals' mortality risk. At higher levels of aggregation (e.g., counties) there are independent effects of income inequality, while at lower levels of aggregation (e.g., census tracts), average area income becomes a more important predictor, and income inequality would be a weaker predictor, of mortality. In our study, we found that the association between income inequality and self-rated health was weakened when Toronto was cut into four sub-areas. Such small areas may be too homogeneous for income distribution to exert an effect independent of individual income.

Moreover, in the United States, Kawachi et al. (Berkman & Kawachi, 2000) argued that if the effects of inequality are in part mediated through differences in state policies and investment in human resources, state, rather than county, may be the more appropriate unit of analysis. We hypothesize that income inequality may play an important role in health through multiple pathways and at different levels simultaneously.

4.3.2 Mutual Influence between Income Inequality and Individual Factors

It is important to note that area and individual characteristics may influence each other. For example, the availability of healthy foods in a neighborhood may influence the dietary behaviors of individuals, and individual behaviors may in turn affect food availability. More specifically, income inequality might cause poor health, however, poor health might influence income. The main mechanism would be that through its influence on ability to work and on earnings (Deaton, 2002), poor health may cause income loss, which in turn increases income inequality. Unfortunately, the methods commonly used in epidemiology today are not well suited to examination of these reciprocal and dynamic relations.

4.3.3 Lag Time between Income Inequality and Health Impact

It seems impossible that the effects of income inequalities are instantaneous. There should be a lag time during which income inequality affects intermediary factors, which in turn affect health. Unfortunately, the lag time for the effect of income inequality is virtually unknown. Blakely et al (1999) specifically examined possible lag times in the association of income inequality with self-rated health. They showed that income inequality measured up to 15 years previously was more strongly associated with self-reported health than contemporary measurement. However, the failure of that study to take into account movement of persons between areas over the time period of interest (misclassification of exposure) prevented it from identifying any time lag.

4.4 Limitations of Our Study

Several factors should be considered in the interpretation of these results.

1. A methodological limitation of the present study is that we failed to take into account the complex design effect due to cluster sampling used by the Ontario Health Survey 1996-97. We did consider the cluster effects within public health units, but not within enumeration areas or within households. Such detailed low-level information is not available in public-use data.

2. The data are cross-sectional, which limits any inferences regarding causation. There might be bi-directional effects; as noted earlier, high income inequality seems to be associated with poor health, while poor health might cause income loss, which in turn widens income inequality.

3. Self-reported fair/poor health. A major concern in the present study is the significance and interpretation of the outcome variables. Although self-reported health status, widely used in European, and more and more in American studies, is a useful indicator of the health conditions of a population, it is a subjective and imprecise measure of health, and it could reflect a person's general perception about the quality of life. However, a review of 27 studies has shown that even this simple measure has strong predictive validity for mortality (Idler & Kasl, 1997).

4. In our study, data on income inequality are not adjusted for taxes, because such information is not available in the 1996 Census. Using unadjusted Gini coefficients could overestimate the true degree of income inequality. However previous work suggests that adjustment of income data makes little difference in the relation between income inequality and health. For example, based on

sensitivity analysis, Kawachi and Kennedy concluded that the income inequality/mortality link in the US was unlikely to be explained by any biases resulting from not adjusting for taxes (Kawichi & Kennedy, 1997).

On the other hand, relative income would be associated with social rank. People with low income may be in a low social position, resulting in psychosocial stress. If disparities in income result in poor health through direct psychological pathways, adjusted income-inequality may have little effect on the association, since poor people are still poor and rich people are still rich after adjusting for taxes.

5. Reporting bias and information bias

Our study may be subject to reporting bias. For example, people with high income may be more likely to report good health, while people with low income may be more likely to report their health as poor, whatever their physical states are, especially in areas with high income inequality. Such reporting bias may lead to overestimation of the association between income inequality and health.

Moreover, in our study it may have introduced misclassification of the "exposure". As noted earlier, income inequalities in Canada have increased in the last generation. Given a certain lag time during which income inequality affects health, if the earlier gap in income distribution across areas was narrower than that in 1996, use of the Gini coefficient measured contemporaneously may bias the estimates of the association.

6. Selection bias

The OHS 96/97 survey does not include persons living on Indian Reserves, Canadian Forces bases, and in extremely remote areas of Ontario. Residents of institutions or collective dwellings, homeless persons, and those without access to a telephone are also not covered by the survey. Thus, our results may be subject to selection biases if the association of income inequality with self-reported poor health varied for excluded people.

4.5 Implications for Policy and Future Research

4.5.1 Implication for Policy

In Canada, there is some evidence that income inequality has been increasing in the last generation (Yalnizyan, 1998). For example, between 1981 and 1996, 60% of Canadian families with dependent children experience a real decline in their average earnings from the market. The real earnings of the bottom 20% of families were cut in half over this period. In 1981 the poorest 20% of the population made the equivalent of about $12,000 a year from work on average. By 1996 the average income from earnings for this group had fallen to just under $6,000. The reason was that a growing number of families have no earners. Moreover, the evidence that the rich are getting richer and the poor are getting poorer is most striking among men. Over the 1980s, the annual amount earned by the poorest 30% of employed men fell by 13%. The best paid 10%, meanwhile, saw steady improvement: an increase of 4.3% in their annual earnings over the 1980s.

Wilkinson (1996) suggested that psychosocial pathways exert an important influence on health in developed nations such as Canada. If disparities in income do play a powerful role in health mainly through psychosocial stress, income redistribution from rich to poor may have little effect on the association, since income redistribution would only improve material conditions for the poor and leave relative deprivation unchanged. We believe that a redistribution in income will have the greatest positive effect on poor people's health, but this is through improving "material" standard for those who are worse off. Hence policy-makers may try other different ways to close the market income gap. Social policies could include: providing an adequate standard of living for poor people, increasing minimum wages to protect those on low income, and ensuring access to educational, training, and employment opportunities especially for those such as the long-term unemployed, removing barriers to access to health and social services and creating jobs.

4.5.2 Further Considerations

1. From a policy perspective there is an increasing interest in ascertaining the level at which interventions should be targeted. Thus further studies examining income inequality at different levels of geographic aggregation will continue to advance our understanding of the material and psychosocial processes linking income inequality to health.

2. Additional studies are needed to identify potential confounding factors. It is not clear which factors are confounders and which are possible causal pathways in the association between income inequality and individual health. For example, other factors may play an intermediary role, such as the density of

physicians and the level and proximity of emergency medical services available to area residents. A recent ecological study at the state level in the US found that both primary care and income inequality exert a strong and significant direct influence on life expectancy and mortality; this influence persisted after controlling for smoking. Primary care is one pathway through which income inequality could influence population-level mortality (Shi & Starfield, 2000).

3. More investigation needs to be done to identify the lag time during which income inequality affects those intermediary factors, which in turn affect health.

4. Interactions between area characteristics and other individual factors have been less commonly investigated. Our study suggested that joint effects on health of income inequality and other individual factors such as individual income should be further investigated.

5. Income inequality may not be associated with all diseases. More precisely, associations between income inequality and specific health outcomes should be further explored. For example, living in an area with high income inequality would be a source of stress that may be particularly relevant for stress-related health outcomes such as mental disorder.

4.6 Conclusion

Our study suggested that income inequalities at public health unit level were modestly, but significantly associated with an adverse impact on self-reported health independent of the effect of individual income. Controlling further for median area income had little effect on the association. In addition, our findings suggested that the association affected only those people with low and middle income, although this difference did not reach statistical significance. Our findings suggested that we should be concerned with reducing the proportion of the population who are worse off.

It remains possible that other area characteristics such as impaired social relationships may also play a role on health. Further inquiry into the theoretical basis and conceptual framework of the relation between income inequality and health will enhance our understanding of this area.

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Appendix A Measures of Income Distribution

Gini Coefficient

The Gini coefficient is one of the most commonly used indicators of income inequality. The Gini is derived from the Lorenz curve, which is a graphic device for displaying the cumulative share of total income accruing to successive income intervals. The Gini coefficient quantifies the area between the Lorenz curve and the diagonal line of equality as a proportion of the entire area under the diagonal. Shryock (1976) provided the following formula.

$$\text{Gini} = \left(\sum_{i=1}^{n} X_i Y_{i+1}\right) - \left(\sum_{i=1}^{n} Y_i X_{i+1}\right)$$

where: X_i = cumulative proportion of households

Y_i = cumulative proportion of income

Atkinson's Index.

The Atkinson Index is one of the few inequality measures that explicitly incorporates normative judgments about social welfare (Atkinson, 1970). The index is derived by calculating the so-called equity-sensitive average income (Y_e), which is defined as that level of per capita income which, if enjoyed by everybody, would make total welfare exactly equal to the total welfare generated by the actual income distribution. The equity-sensitive average income is given by:

$$Y_e = \left(\sum_{i=1}^{n} f(Y_i)\, Y_i^{1-\varepsilon}\right)^{1/1-\varepsilon}$$

Where Y_i is the proportion of total income earned by ith group, and ε is the so-called inequality aversion parameter. The parameter ε reflects the strength of society's preference for equality, and can take values ranging from zero to infinity. When $\varepsilon > 0$, there is a social preference for equality (or an aversion to inequality). As ε rises, society attaches more weight to income transfers at the lower end of the distribution and less weight to transfers at the top.

The Atkinson Index (I) is given by:

$$I = 1 - Y_e / \mu$$

Where μ is the actual mean income. The more equal the income distribution, the closer Ye will be to μ, and the lower the value of the Atkinson Index. For any income distribution, the value of I lies between 0 and 1.

Theil's entropy measure.

A measure of inequality proposed by Theil derives from the notion of entropy in information theory. The entropy measure, T, is given by:

$$T = \sum_{i=1}^{n} S_i [\log S_i - \log (1/n)]$$

Where S_i is the share of the ith group in total income, and n is the total number of income groups. The index has a potential range from zero to infinity, with higher values (greater entropy) indicating more equal distribution of income.

Other measures: The decile ratio is calculated by taking the income earned by the top 10% of households and dividing by the income earned by the bottom 10% of households. The proportions of income earned by the bottom 50%, 60%, and 70% of households are calculated from the cumulative percentage distributions of total aggregate income in each area.

Appendix B Gini Coefficient and Lorenz Curve for Ontario Data, 1996

Table B Gini Coefficient Calculation for Ontario Data, 1996

Household income of all private households	Numbers of Households	Proportion of Households	Income	Proportion of income	Cumulative Proportion of Households (%)	Cumulative Proportion of Income (%)	$X_i Y_{i+1}$	$Y_i X_{i+1}$
					X	Y		
Under $10,000	251385	0.0640551	1.257E+09	0.0058992	6.405513	0.589924		
$ 10,000 - $19,999	553265	0.1409768	8.299E+09	0.0389503	20.503197	4.4849573	0.0028728	0.0012095
$ 20,000 - $29,999	475580	0.121182	1.189E+10	0.0558021	32.621397	10.065164	0.0206368	0.0146306
$ 30,000 - $39,999	453685	0.115603	1.588E+10	0.0745262	44.181694	17.517788	0.0571455	0.0444696
$ 40,000 - $49,999	425920	0.1085282	1.917E+10	0.0899554	55.034514	26.513328	0.1171404	0.0964083
$ 50,000 - $59,999	385650	0.098267	2.121E+10	0.0995503	64.861218	36.468362	0.2007019	0.1719687
$ 60,000 - $69,999	334690	0.085282	2.175E+10	0.102104	73.389417	46.678764	0.3027641	0.2676392
$ 70,000 - $79,999	266925	0.0680149	2.002E+10	0.0939588	80.190903	56.074639	0.4115285	0.3743212
$ 80,000 - $89,999	204200	0.052032	1.736E+10	0.0814632	85.3941	64.220957	0.5149937	0.4788443
$ 90,000 - $99,999	147715	0.0376391	1.403E+10	0.065862	89.15801	70.807157	0.6046513	0.5725813
$100,000 and over	425510	0.1084237	6.22E+10	0.2919284	100	100	0.8915801	0.7080743
Total	3924525	1.0	2.13066E+11	1.0			3.12	2.73

$$\text{Gini} = (\sum_{i=1}^{n} X_i Y_{i+1}) - (\sum_{i=1}^{n} Y_i X_{i+1}) = 3.12 - 2.73 = 0.39$$

Figure B Lorenz Curve for Ontario Data, 1996