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ANALYSIS OF LOCAL MORTALITY VARIATION: A CANADIAN CASE STUDY†

*Kao-Lee Liaw** *Michael V. Hayes*** *Ronald G. McAuley****

INTRODUCTION

Although it is well documented that overall mortality and its interprovincial variation have decreased substantially in Canada since the 1930s (Field 1980), relatively little is known about the spatial variation in mortality at the local level. Yet the need for information concerning the health status of small area populations is widely recognized (Mooney and Rives, 1978; Scott-Samuels, 1984; Morgan and Chin, 1983). The increasing public awareness of, and concerns over, matters of health and health care, and rising fiscal pressures on governments for effective allocation of public resources, will likely result in an increased demand for localized health-related information. While mortality data do not, by themselves, provide a complete indication of health status, they do contribute to our understanding of local variations in health status.

The little information that is available suggests that, in Canada, small area differences in mortality are surprisingly large and persistent and, hence, deserve careful analysis. Wilkins (1980) found that, in Montreal in the mid-1970's, the disparity in life expectancy at birth between the wealthiest areas and the disadvantaged "Lower City" was seven years, equivalent to the difference between Sweden and third-world countries like Suriname and Guyana. Wigle and Mao (1980) found differences in life expectancy at birth of six years for males and three years for females between persons in the highest and lowest income quintiles of census

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* Ph. D. and Professor of Geography, McMaster University.
** Graduate student in Geography, McMaster University.
*** Ph. D. and Professor of Family Medicine, McMaster University.

tracts in Canadian cities.

Measurement and explanation of local mortality are by no means easy tasks. Measurement problems arise from the lack of sufficiently detailed data at the local level, the smallness of the underlying at-risk populations, and the lack of correspondence between population data and vital statistics in terms of the age-by-time framework. The explanation of mortality variation is hindered by the high turnover rate of local residents, the long period between the onset of major causes of death such as cancer and heart diseases and the fatal event, and the crudeness of socioeconomic indicators available at the local level.

In spite of these difficulties, the magnitude of disparity in mortality experience between different localities, suggested by Wilkins and others, indicates that small area analysis of mortality deserves greater attention. The purpose of this paper is to present an analytical approach to identifying and explaining local mortality variations, using the data of the Hamilton region.

THE DATA

A listing of all deaths occurring between January 1, 1980 and December 31, 1982 in which the decedents' last place of residence was an address in the Regional Municipality of Hamilton-Wentworth was obtained from the Ontario Ministry of Health. It contained the following information: age at death in single years, sex, cause, year of death, and the death certificate registration number. Approximately 11,000 certified deaths occurred in this population of about 450,000. Registration numbers were then used to identify the original death certificates in the Office of the Registrar General, from which the address of the last place of residence was identified. This address was then identified in the Street Index of Hamilton (Statistics Canada 1983b) to assign deaths to individual census tracts. A record was also made as to whether or not the last place of residence was an institution. To date, only the census tract coding for the two most populous municipalities in the region – the Cities of Hamilton and Stoney Creek – has been completed. Ignoring the three lightly populated tracts, our study area includes 96 census tracts in these two cities. We call this study area the Hamilton region for short.

In this report, we focus on the analysis of mortality by census tract from all causes among males in the 55-64 age group. In this group, both the number of deaths and the size of the at-risk population are fairly large (median at-risk population = 180; median number of deaths = 9). Thus the possibility of random variation obscuring any systematic pattern we might uncover is reduced. While our chosen age interval is rather wide, a more narrow interval would compel us to merge the census tracts into larger units and hence lose too many degrees of freedom for statistical inference.

The data on the at-risk population is taken from the 1981 Census Profile Series A, which is based on the enumeration of the 1981 population census taken on June 3 (Statistics Canada 1982).

THE SPECIFICATION AND CHARACTERIZATION OF OBSERVED DEATH RATES

Let D_i be the number of male deaths in the 55-64 age group that occurred in census tract i during the three-year interval between January 1, 1980 and December 31, 1982. Note that actually we have excluded from D_i the few deaths (23 out of 850) that occurred in institutions, because the attributes of the residents in institutions are not used by Statistics Canada in reporting the socioeconomic information of the census tracts.

Let P_i be the number of male residents in census tract i on June 3, 1981 in the same age group. We compute the estimated annual male death rate (M_i) of the 55-64 age group in census tract i according to:

$$M_i = (D_i/Y)/P_i \tag{1}$$

where Y = 3 is the number of calendar years. Referring to the Lexis diagram in Figure 1, P_i includes all males whose life lines cross the vertical line segment EF, whereas D_i includes all males whose life lines are terminated somewhere within the rectangle ABCD. Clearly, eq. (1) mismatches the two sets of life lines. The problem is not very important here because of our long age interval. However, when a short age interval is used, D_i should be defined as the number of deaths in the parallelogram A′ B′ C′ D′. Of course, to obtain the value of the more appropriately-specified

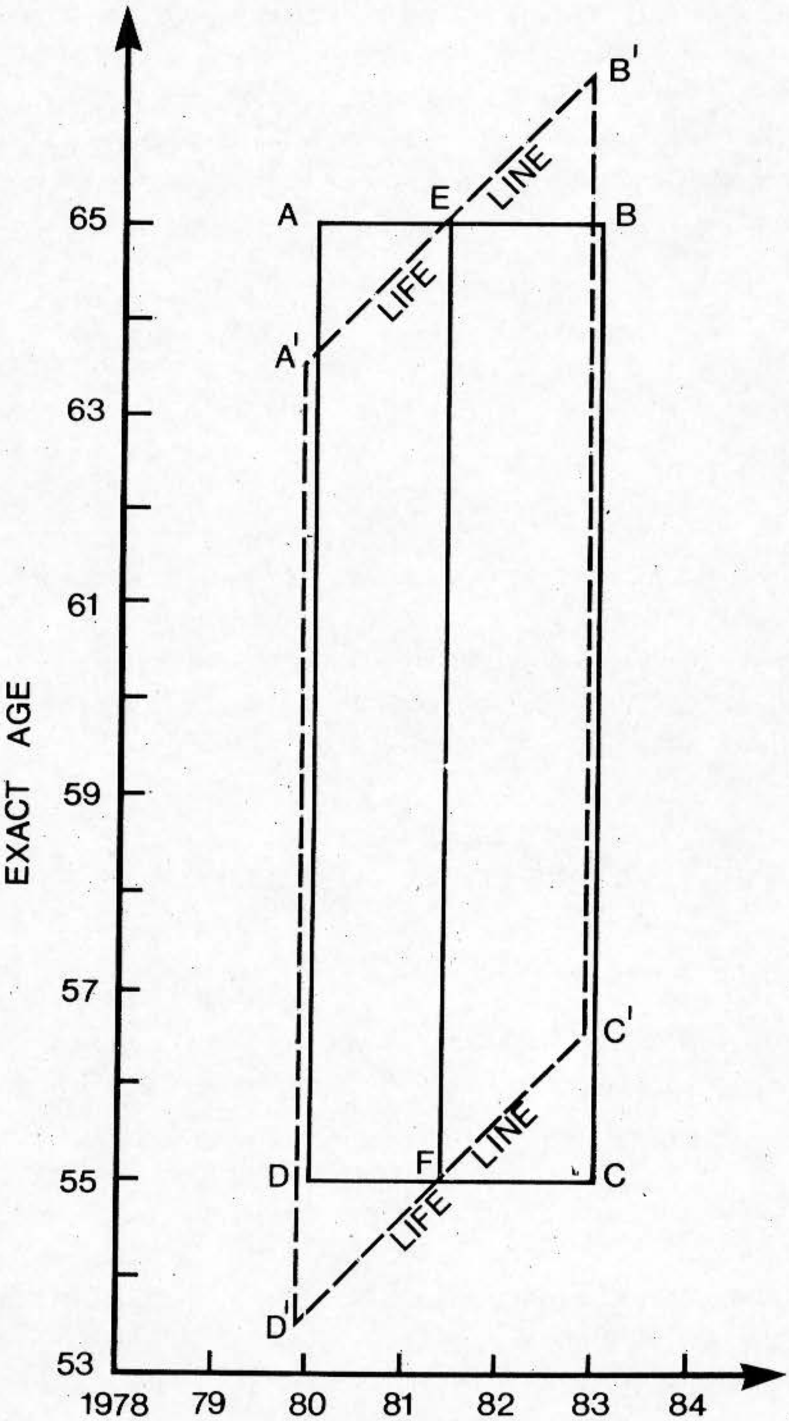

Figure 1 The Lexis Diagram for Matching Deaths to the At-Risk Population.

Table 1. The Frequency Distributions of the Census Tracts (C. T.) in the Hamilton Region in Terms of the 1980-82 Average Annual Death Rate of the Males in the 55-64 Age Group.

(1) Death Rate Per 1000	(2) Number of C. T.	(3) Adjusted Number of C. T.	(4) Number Deleted	(5) Percent Deleted	(6) Relative Freq.	(7) Adjusted Relative Freq.
0 – 4	3	1	2	67	3.1	1.3
5 – 9	11	7	4	36	11.5	9.2
10 – 14	24	19	5	21	25.0	25.0
15 – 19	30	26	4	13	31.3	34.2
20 – 24	15	13	2	13	15.6	17.1
25 – 29	6	6	0	0	6.3	7.9
30 – 34	3	1	2	67	3.1	1.3
35 – 39	0	0	0	0	0.0	0.0
40 – 44	3	2	1	33	3.1	2.6
45 – 49	1	1	0	0	1.0	1.3
Total	96	76	20	21	100.0	100.0

Note: In column (3), the census tracts with less than 100 people in the at risk-population or with no observed deaths are not included. Column (6) is based on column (2), and column (7) on column (3).

number of deaths, the information on the birth date (or at least the birth year) of the decedents has to be used.

The mean and median death rates for all census tracts are 17.0 and 16.0 per 1,000, respectively. The frequency distribution is unimodal and somewhat positively skewed (Table 1). Contrary to our finding, Saveland (1983), using improper (i.e. unequal) class intervals, incorrectly inferred from the 1971 data that the mortality distribution is bimodal.

The standard deviation is 8.5 per 1,000, implying that the coefficient of variation is 50 percent. If we ignore the census tracts with less than 100 people in the at-risk population or with no observed deaths, we find that the maximum death rate is 45 per 1,000, which occurs in a downtown area with very low median family income, and that the minimum death rate is 4 per 1,000, which occurs in a relatively high-income area above the Niagara Escarpment.

Figure 2 shows that all census tracts with death rates higher than 24 per 1,000 are located in the area below the Niagara Escarpment, where the landscape is dominated by heavy industry and low-income housing. Well-known high-income areas (e.g. Westdale, West Mountain, and the Mountain Brow along the Escarpment) tend to have relatively low mortality level.

EXPLANATION OF THE INTRAURBAN MORTALITY VARIATION

The Model and the Method of Estimation and Inference

The spatial pattern of the death rates shown in Figure 2 is partly due to the underlying pattern of the probabilities of dying and partly due to random errors. The random errors may be due to the pure chance variation in the death process, to errors in data collection, or to the heterogeneity of the at-risk population within each census tract. It is the underlying pattern of the probabilities of dying that we wish to explain.

Let m_i be the probability that a male in the 55-64 age group in the ith census

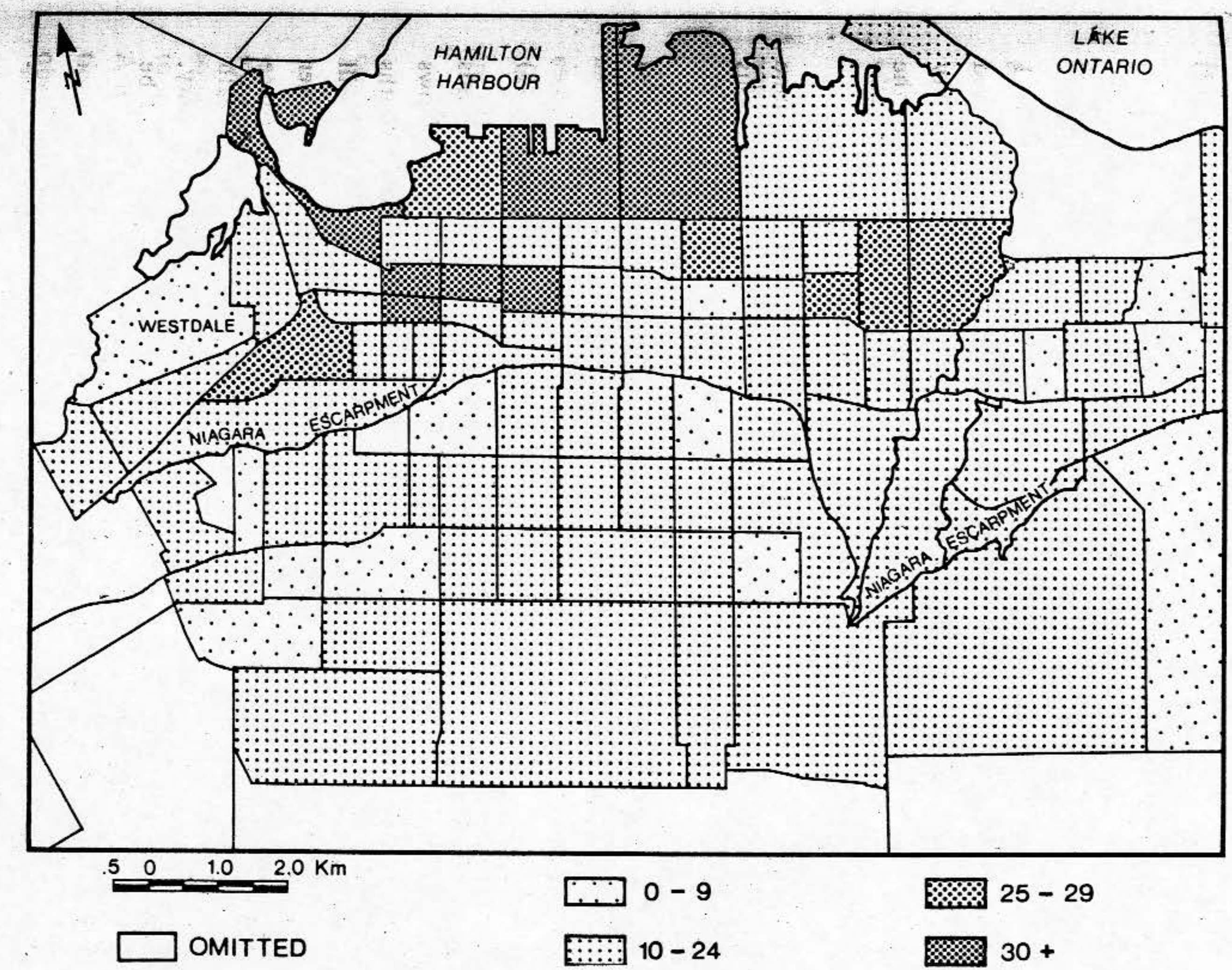

Figure 2. The Spatial Pattern of the Annual Death Rate per 1000 of Males in the 55 - 64 Age Group in the Hamilton Region, 1980 - 82.

tract will die within a year. We assume that m_i is related to a set of q explanatory variables $(X_{i1}, X_{i2}, \ldots, X_{iq})$ according to the following logit model:

$$m_i = \exp(\underset{\sim}{\beta}' \underset{\sim}{X}_i)/(1 + \exp(\underset{\sim}{\beta}' \underset{\sim}{X}_i)) \tag{2}$$

where

$$\underset{\sim}{\beta}' \underset{\sim}{X}_i = \beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_q X_{iq} \tag{3}$$

$\underset{\sim}{\beta}'$ is a 1–by–(q + 1) vector of unknown parameters, and $\underset{\sim}{X}_i$ is a (q + 1)–by–1 vector containing the value one and the values of q explanatory variables observed in the ith census tract. A desirable property of this model is that the probability of dying is always bounded between zero and one for any combination of the values in the explanatory variables.

To link the observed death rates to the underlying probabilities, we assume that the expected value and the variance of the observed death rate in each census tract are such that

$$E[M_i] = m_i \tag{4}$$

and

$$\mathrm{Var}[M_i] = \sigma^2 m_i (1 - m_i)/P_i \tag{5}$$

where σ^2 is another unknown parameter. If the death process within each census tract can be represented by *independent* events, then the number of deaths follows the simple binomial law and the value of σ^2 equals one. However, if the deaths are mostly due to contagious diseases, then the events of death in a locality will be positively correlated so that the value of σ^2 is greater than one. On the other hand, if the death of some person leads to preventive measures that tend to reduce the risk of dying of other persons in the same locality, then the events of death will be negatively correlated so that the value of σ^2 is less than one. In reality, deaths may or may not be independent events and the value of σ^2 should be estimated directly from the empirical data.

To estimate the "regression" parameters in $\underset{\sim}{\beta}'$, we use the maximum quasi-likelihood method which was first introduced by Wedderburn (1974) and then extended by McCullagh (1983). An advantage of this method over the well-known maximum likelihood method is that we do not have to know the exact form of the joint probability distribution of the observations in the sample. This method is also better than the ordinary least-squares method, because it assigns greater weights to more reliable observations (e.g. the death rates computed from relatively large at-risk populations). A detailed exposition of the application of this method to a logit model is found in Liaw and Ledent (1987).

To estimate the dispersion parameter σ^2, we adopt the following weighted residual mean square recommended by McCullagh (1983):

$$S^2 = \sum_{i=1}^{N} W_i (M_i - m_i)^2 / (N - q - 1) \tag{6}$$

where weights are such that

$$W_i = P_i / m_i (1 - m_i) \tag{7}$$

and N is the number of observations. Note that here m_i and W_i are evaluated at the maximum quasi-likelihood solution.

To evaluate the relative importance of the explanatory variables in terms of the likelihood criterion (Liaw and Bartels, 1982), we use the t-ratios, which are the estimated regression coefficients divided by the corresponding asymptotic standard errors. The greater the magnitude of the t-ratio, the more important the corresponding explanatory variable.

To evaluate the goodness-of-fit of the whole model, we use the weighted coefficient of determination:

$$W^2 = 1 - S^2 / S[0]^2 \tag{8}$$

where $S[0]^2$ is the weighted total mean square (i.e. the weighted residual mean square of the "null" model that constrains all regression coefficients except β_0 to be zero). The value of W^2 ranges from zero for a poor fit to one for a perfect fit. A less desirable index of the goodness-of-fit is the simple coefficient of determination (R^2), which is the square of the simple correlation coefficient between the observed and predicted values of the dependent variable.

We use the nonlinear estimation program BMDP3R (Dixon, 1981) to implement the maximum quasi-likelihood method. This program is particularly helpful at the exploratory stage, because it allows the user to plot the observed and predicted values of the dependent variable as well as the residuals against any variable. The plots may suggest the need for transforming some explanatory variables or for searching for some missing variable that may have caused a systematic bias in the residual.

The Choice of Explanatory Variables

The data on numerous socioeconomic variables at the census tract level are available in the 1981 census publications and tapes. From the data in the 1981 Census Profile Series B (Statistics Canada 1983a), we have computed the values of 15 potentially useful explanatory variables. The choice of these variables are based partly on the literature and partly on our desire to use attributes that are easily observed (e.g. the housing condition) to enhance the utility of them as indicators of risk. Since most of these variables have turned out to be statistically unrelated to the spatial variation in mortality, we will not burden the reader with the description of all of them. Instead, we will focus on only three variables that have been found by others to be related to mortality variation in Canada.

The first variable is the logarithm of median family income. Wigle and Mao (1980) have analysed deaths in 1971 among residents of all metropolitan areas in Canada by census tract of residence and related various measures of mortality to the median family income. By ranking the census tracts in terms of median family income, they found that the difference in life expectancy at birth between the highest and lowest quintiles was about 6 years for males and 3 years for females. Wilkins (1980) suggests that the difference would have been greater if the nominal income had been adjusted for the large variation in the cost of living among the metropolitan areas. Since our plot of death rate against income shows a curvature greater than that of a negative exponential function, we use the natural log-transformation, which makes the odds of dying a power function of median family income.

The other two variables are divorcehood and widowhood. In their study of the 1975-77 Canadian population, disaggregated by marital status, Adams and Nagnur (1981) show that the males who were divorced or widowed had a life expectancy 12 years less than that of the married males; and that the females who were divorced or widowed had a life expectancy six years less than that of the married women. To the extent that divorcehood and widowhood vary among the census tracts within a metropolitan area, we expect these variables to be positively related to the probability of dying. Due to the lack of a detailed age break down in our data source, we compute divorcehood by dividing the number of people who were divorced by the number of people who were older than 14 years. Similarly, widowhood is computed by dividing the number of widows and widowers by the number of people who were older than 14 years. While this approximation is rather crude, this was the best available estimate for each variable.

The Estimation Result

We began the estimation procedure by fitting the null model to the data and plotting the residuals against the 15 potentially useful explanatory variables. These bivariate plots suggested that the death rate is negatively related to the log of income and positively related to widowhood and divorcehood. They also suggested that the death rate is positively associated with such variables as the proportion of adults with less than nine years of education, the unemployment rate of males aged 25+, and the proportion of economic families with low income. The log of income was found to be most strongly related to the death rate.

In the second step, the log of income was introduced into the model. The result is shown as Specification 1 in Table 2. The t-ratio of –8.7 indicates that there is a highly significant negative relationship between the probability of dying and the median family income. The weighted coefficient of determination is 0.46, implying that close to 50 percent of the variation in the observed death rates can be explained by only one variable. Unfortunately, the plots of the residuals no longer suggested a positive or negative association between the death rate and any of the remaining 14 variables. Only widowhood seemed to be vaguely related to the dependent variable.

In the third step, the model was expanded to include widowhood and the result is reported as Specification 2 in Table 2. Although the negative effect of the log of income remained highly significant (t = –6.9), the positive effect of widowhood is not significant at all (t = 0.8). Although the R^2 increased slightly, this specification resulted in a slight decrease in the weighted coefficient of

Table 2. Summary Result of Applying the Logit Model to the Explanation of the Spatial Variation in the Annual Death Rate of the Males in the 55-64 Age Group in the Hamilton Region: 1980-82

Explanatory Variable	Specification 1	Specification 2	Specification 3
Ln (Income)	–0.575 (–8.7)	–0.540 (–6.9)	–0.547 (–5.3)
Widowhood		0.063 (0.8)	0.065 (0.8)
Divorcehood			–0.010 (–0.1)
S[0]**2	0.627	0.627	0.627
S**2	0.336	0.338	0.342
W**2	0.46	0.45	0.45
R**2	0.48	0.49	0.49
Deg. of Freedom	94	93	92

Note: The values in parentheses are the t-ratios, and those above them are the beta weights. For an explanatory avriable, the magnitude of the t-ratio reflects the likelihood of the existence of relationship with the dependent variable; whereas the magnitude of the beta-weight indicates the strength of average relationship with the dependent variable in terms of standardized units (see section 2 in the Appendix for more information).

determination (W^2 = 0.45). The plots of the residuals against the remaining variables all failed to show any systematic alignment.

In the final step, the model was further expanded to include divorcehood. From Specification 3 in Table 2, we find that the lack of association between the probability of dying and divorcehood *in the context of income and widowhood* is indeed clearly indicated by the t-value of −0.1. The values of W^2 and R^2 remain identical to those of Specification 2. In the context of the two variables on marital status, the negative effect of the log of income remains highly significant.

The weighted mean squares $S[0]^2$ and S^2 in all three specifications are artificially small and should be adjusted by a factor of three, because we have used the average number of deaths over the three-year period 1980-82 to estimate the number of deaths in 1981 (see eq. (1)). The adjusted values of S^2, which are taken as the estimates of σ^2, are all very close to one, indicating that the deaths within the census tracts in the Hamilton region are *independent* events.

In summary, for the males in the 55-64 age group, the spatial variation in the probability of dying appears to be similar to the spatial variations of several socioeconomic variables, when we use a bivariate analysis. However, in a multivariate framework, only the spatial variation in the log of median family income turns out to be strongly related to the spatial variation in the probability of dying.

SUGGESTIONS FOR FURTHER RESEARCH ON LOCAL MORTALITY VARIATION

Due to the smallness of local populations and the large variation in local age compositions, imprecision in measuring death rates can defeat small area mortality research from the start. Precision can be improved through the use of a Lexis diagram to check if the mortality and population data sets are matched properly. If an age interval of less than five years is chosen, the information on the *birth date* of each decedent is essential to allocating the death to an appropriate parallelogram. [Note that the provincial death registrations (statements) in Canada do contain the information on birth date and birth place.] With respect to the at-risk population in a post-censal year, one should look for an up-to-date enumeration result of the local government, because the interpolation or extrapolation of the census populations for local areas may yield quite unreliable figures. Unfortunately, not all municipalities enumerate their residents annually.

With respect to the measurement of explanatory variables, we emphasize that many of the figures published by Statistics Canada for local areas are too aggregated to be of any use. For example, the data on marital status at the census tract level in the 1981 Census Profile Series B show the numbers of widowed and divorced individuals only for the 15+ age group. In our preliminary analysis of the mortality in the Hamilton region, we divide these numbers by the local populations in the same broad age group. The resulting rates of widowhood and divorcehood may be so perversely affected by the differences in age composition among the census tracts that they become misleading indices of the probabilities of being widowed or divorced. We suspect that the unimportance of these two variables in our study is probably due to the crudeness of the data on marital status. Fortunately, we have now learned that more disaggregated data can be ordered from Statistics Canada on magnetic tapes.

One should also attempt to incorporate data from various sample surveys – particularly those on smoking and drinking behavior. With respect to the quality of environment, there are too few monitoring stations to yield useful information for local areas so that the researcher who is interested in the effects of environmental hazards may have to look for intriguing clues in the residuals of a multivariate statistical model that presumably includes all other relevant factors.

The problem of time lag cannot be ignored. The cause and effect in mortality may involve an unknown period of delay. When the delay is long, the migration process may relocate sufficient number of people so that cross-sectional (or even time-series) analysis using small geographical areas as the units of observation may not be able to reveal the causal relationship. A very expensive way of dealing with this problem is to construct a longitudinal data base. If one wants to use less expensive data to study the long-term effect of the environment, one may disaggregate both death and population data by place of birth and concentrate only on the "stayers" in different localities. Since both the death registrations and the census questionnaires in Canada contain the information on birth place, a persistent researcher may get the job done. Of course, return migration may reduce the value of this approach.

Finally, when the basic areas of observation are small and numerous (e.g. the census tracts in the Toronto Census Metropolitan Area), aggregation into larger units in terms of the variables that are likely to be related to the probability of dying (e.g. income, marital status, or even the distance to sources of pollution) will reduce the extent of random variation. Also, aggregation may make the at-risk populations large enough to allow a meaningful study of cause-specific mortality. We plan an aggregate analysis of our data at the next stage of this research.

In conclusion, although the problems encountered in the analysis of local mortality variation may appear overwhelming, we hope that our limited experience and suggestions would help other population geographers in conducting mortality research.

APPENDIX

We prepare this appendix in response to two comments of a thoughtful reviewer: one about the need for a theoretical framework in choosing the explanatory variables, and the other about the meaning of the coefficients associated with these variables.

THEORETICAL FRAMEWORK

Although we agree that it is desirable that the choice of explanatory variables be based upon theory, two points seem relevant. First, there is no tenable single theoretical perspective from which to approach analysis of local mortality. While environmental determinism has an obvious appeal, the theoretical underpinnings of this approach are suspect and there is little empirical evidence of mortality in the general population to support this position. (This is not to deny the importance of localized environmental effects such as the great London fog or the Chernobyl disaster.)

More commonly, theoretical perspectives on patterns of mortality focus upon the social characteristics of the population(s) of interest rather than upon the role of space *per se*. The Black Report (1982) identified three types of theoretical explanations for observed relationships between health status and social class in the U.K.: (1) theories of natural or social selection; (2) materialist or structuralist explanations; and (3) cultural/behavioural explanations. Briefly, explanations of the first type suggest that the frailest and biologically weakest members of society are also those least capable of achieving high socioeconomic status. Thus it is not that social class "causes" mortality but that those biologic characteristics that "cause" poor health status also determine social class. Explanations of the second type suggest that differences in income, arising from differential rewards to occupational groups and related to levels of educational attainment, are indicative of differences in the range of individual choice and/or relative advantages enjoyed by different social groups. Those with the most advantage, those who have the greatest range of choice, have the best chance of survival. The last type of explanation emphasizes the importance of personal factors, such as dietary practices, substance use/abuse (i.e. tobacco, alcohol, etc.), and individual attitudes and beliefs.

The report identified material/structural explanations as accounting for most of the observed difference in health status between groups, although behaviour and natural selection are also thought to contribute to it. To the extent that residential mobility (or the lack of it) maps social class distinction into geographical segregation, these theoretical perspectives may prove useful for the study of local mortality variation.

The second point is that what is desirable is not always what is available. Our choice of explanatory variables was limited to what was available from the 1981 Canadian census. This source does not include information about individual behaviour, the quality of the local environment, or other factors that might play a fundamental role in shaping the patterns we observe.

INTERPRETATION OF THE COEFFICIENTS

The roles of the coefficients in equation (3) are as follows. β_0 serves to match the overall levels of predicted probabilities of dying and observed death rates; conceptually, it is analogous to the constant term in linear regression. The coefficient associated with the jth explanatory variable (β_j) helps to determine the marginal effect of the variable on the probability of dying according to:

$$\frac{\partial m_i}{\partial X_{ij}} = \beta_j m_i (1 - m_i) \tag{A1}$$

When two explanatory variables (say, X_j and X_k) have the same unit, the relative importance of them, in terms of average intensity, can be evaluated by:

$$\frac{\partial m_i}{\partial X_{ij}} \bigg/ \frac{\partial m_i}{\partial X_{ik}} = \beta_j / \beta_k \tag{A2}$$

However, since the explanatory variables are measured on different units in most applications, it becomes necessary to make the variables comparable before we can evaluate their relative importance in terms of average intensity. Two popular *ad hoc* methods to do so are the uses of elasticity and beta-weight. The elasticity of the probability of dying with respect to the jth variable is

$$(\partial m_i/m_i)/(\partial X_{ij}/X_{ij}) = \beta_j X_{ij} (1 - m_i) \tag{A3}$$

whereas the corresponding beta-weight is

$$(\partial m_i/S_m)/(\partial X_{ij}/S_j) = (\beta_j\ S_j/S_m)\, m_i(1 - m_i) \tag{A4}$$

where S_m is the standard deviation of the dependent variable and S_j is the standard deviation of X_j. The elasticity indicates the percentage change in the dependent variable due to a one percent increase in X_j, whereas the beta-weight shows the effect in standardized units. Since both elasticity and beta-weight vary from case to case, they are usually evaluated only at a representative point (i.e. the centroid). Note that when X_j is measured on an interval scale, the value of the elasticity changes with the arbitrary zero of the scale and hence becomes meaningless. In Table 2 we only report the beta-weights.

All the above-mentioned indices are not worth examining, if the coefficients associated with the explanatory variables are not significantly differently from zero. In other words, the corresponding t-ratios must be so large in magnitude that they are in the "region of rejection" before we become interested in evaluating the relative importance of the explanatory variables in terms of average intensity. In short, if a relationship is unlikely to exist, it is pointless to study its average strength.

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小地方之間死亡率差異之分析

廖 高 禮, *Michael V. Hayes, Ronald G. McAuley*

(中 文 摘 要)

本文以加拿大安大略省漢密爾頓地區爲實例，研討分析小地方之間死亡率之差異。因爲官方的死亡資料不夠詳細，我們花了很多時間首先把個人的死亡登記依地點、性別、和年齡分類，然後把得到的死亡數與相關的人口配合而算出各地的死亡指數。我們也利用非線性的統計方法來解釋漢密爾頓地區內的死亡差異。

我們的主要發現如下：(1)小地方間之死亡差異很大；(2)中位家庭所得能解釋此差異之百分之四十六；(3)其他被我們採用的社經因素，與中位家庭所得合用於多變數模式時，都顯得不重要。

本文報告的只是初步的結果。爲促使小地方死亡差異研究的加强，本文最後提了一些實際的意見供同行的學者參考。

ANALYSIS OF LOCAL MORTALITY VARIATION: A CANADIAN CASE STUDY

(ABSTRACT)

This paper deals with the problems of measuring and explaining local mortality variation, based on a case study of the Hamilton region in the Province of Ontario, Canada. Due to lack of detailed official data, the local mortality pattern is established after we have spent much time in recording information directly from individual death registrations and in matching the number of deaths by age and sex with the relevant at-risk population for each of the 96 census tracts in the Hamilton region. To explain local mortality variation by socioeconomic variables, we use the logit model and the maximum quasi-likelihood estimation method.

We find that local mortality variation is substantial in our study area; that median family income can explain nearly half of the mortality variation among the census tracts; and that other socioeconomic variables (e.g. widowhood and divorcehood), which appear to be significant variables of mortality variation in bivariate and non-spatial analyses, turn out to be insignificant in our multivariate analysis using the logit model.

Our results are by no means definitive. To help promote further research on local mortality variation, we conclude our paper by providing what we hope to be helpful and practical suggestions.