Issues in Developing Indicators for Needs-Based Funding

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The usual caveat, that notwithstanding the comments we have received, we assume full responsibility for the contents of this paper, applies to this work in more than standard measure. Inasmuch as the issues addressed are complex and deep and given that the comments have been so wide ranging and diverse, it has been impossible to satisfy all of them definitively. In that sense, our results constitute a starting point for further debate.

The Manitoba Centre for Health Policy and Evaluation

The Manitoba Centre for Health Policy and Evaluation (MCHPE) is a unit within the Department of Community Health Sciences, Faculty of Medicine, University of Manitoba. MCHPE is active in health services research, evaluation and policy analysis, concentrating on using the Manitoba health data base to describe and explain patterns of care and profiles of health and illness.

Manitoba has one of the most complete, well-organized and useful health data bases in North America. The data base provides a comprehensive, longitudinal, population-based administrative record of health care use in the province.

Members of MCHPE consult extensively with government officials, health care administrators and clinicians to develop a research agenda that is topical and relevant. This strength, along with its rigorous academic standards and its exceptional data base, uniquely position MCHPE to contribute to improvements in the health policy process.

MCHPE undertakes several major research projects every year under contract to Manitoba Health. All projects address substantive issues in health policy, and some, such as this one, address basic science issues in population health research. In addition, MCHPE researchers secure major funding through the competitive grants process. Widely published and internationally recognized, they collaborate with a number of highly respected scientists from Canada, the United States and Europe.

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OVERVIEW

It is widely accepted across Canada that funding for health care should be provided on the basis of need. However, identifying exactly how to measure need is a difficult problem. This report examines one possible way of measuring need in a service area when detailed data is available on utilization patterns in that area. The methodology provides an idealized starting point for needs-based planning in such areas. The model presented here was first developed to look at requirements for physician services in Manitoba. This paper elaborates that methodology to make it more accessible to those interested in the policy question of needs-based funding.

In developing the model, we start by examining a number of measures often tied to requirements for health care resources: demographic, socio-economic and health status. In particular, we examine the mix of age and gender in the population, premature mortality and socio-economic indicators of populations as measured by the Socio-economic Risk Index (SERI). SERI (based on Census measures of socio-economic characteristics of the population) has been developed at the Centre as one measure of need.

Combining indicators such as these into estimates of an area's need for health care evokes a number of nettlesome theoretical and practical problems. Here, we provide a look at models consisting of different combinations of these factors. We use ambulatory physician visits as an exemplary case. One of the problems to which our approach provides a tentative solution is the issue of the how much additional health care should be provided for any increment in a measure of need (i.e. the size of the coefficient linking the measure of need to the amount of health care provided). Put simply, how many more health care resources should an area have for each increment of higher premature mortality, older women, people of low socio-economic status, etc?

The model is based on 58 physician service delivery areas in the Province of Manitoba which are later aggregated into the 12 Regional Health Authorities which the Province proposes as the basis for funding health care. The model is developed in two stages. The first stage examines current utilization patterns based on area characteristics. Identifying a current utilization pattern that is consistent with need, it assigns resources in a way that smoothes out current discrepancies in allocations so that areas are given resources in accordance with the prevailing average utilization patterns. The "averages" are calculated by means of a regression model which takes into account various indicators of need. The effect of the first stage allocation is to give each area a level of resources according to current practices inasmuch as those practices are consistent with need. Four models for adjusting to average utilization levels are explored for the first stage adjustment: age/gender, age/gender/premature mortality, age/gender/SERI and age/gender/premature mortality/SERI. We judge the best model to be the one in which a first stage allocation is based on age, gender and socio-economic status.

While current practices appear to take need for physician services (as measured by age, gender and SERI) into account to a significant degree, the fit between another measure of need (premature mortality) and current utilization is not extremely tight. Accordingly, we introduce a second stage reallocation based on the latter measure. That stage reallocates to needier regions by explicitly taking into account differences in premature mortality rates across regions. Areas having higher premature mortality than average are allocated additional resources, those less needy are allocated fewer. This second stage reallocation may not be necessary in other health care sectors (such as acute hospitalizations) if current allocations are found to very closely related to the relevant measures of need. Thus, on a stage by stage basis, the methodology can be adapted to sector specific planning.

The size of the additional reallocations when additional reallocation is required for differences in premature mortality is based on a coefficient derived from the analysis in the first stage. Thus, the two stage model combines the three major categories of need identified in the literature (demographic, socio-economic and health status) and provides a coefficient for tying differences in average premature mortality rates to reallocations. And because it is based on a complex regression model, the reallocation also takes into account the fact that need in each age/gender stratum may vary across different levels of socio-economic status - a factor missing in most needs-based models.

Implications for needs-based funding methods

In constructing this method of resource allocation, we ran into a number of issues with implications for needs-based funding methods. One of these identifies a potential problem in the common practice of using age and gender as an initial indicator of need. We find that using the age/gender distribution of the population as the only adjuster for need in Manitoba introduces potential biases into the analysis. Since areas of high need in Manitoba (as measured by health status) tend also to have younger populations, and usage patterns in different areas of the Province may vary across the age/gender strata as well as according to socio-economic status, there are potential problems in using a simple age/gender adjustment of actual use as a "baseline" from which to reallocate.

For example, suppose that existing patterns of usage of physician visits do, to a moderate extent but imperfectly, take into account need for services based on differences in socio-economic status. Say for example, that the poorest areas have modestly higher levels of physician visits for young children than better off areas in the Province. Since the poorest areas are relatively small in number and size relative to the rest of the Province, a simple age/gender adjustment to calculate average allocations by age/gender categories will assign these poorer areas fewer visits than they currently enjoy for young children. But given that the populations of these poorer regions are much younger than the Provincial average, such an initial adjustment could create a "baseline" which allocates poorer younger regions fewer resources than they already consume. In other words, age/gender adjustment may not be normatively neutral relative to acceptable measures of need. Consequently, it may not provide a neutral baseline for subsequent adjustments that factor additional measures of need into the equation. Were this new baseline to be accepted as a "neutral" baseline, it would then create the impression that any subsequent needs-based reallocations are very substantial.

The underlying issue turns on the possibility that utilization across age/gender strata may well vary as a function of some underlying measure of need (such as socio-economic status or premature mortality) and the distribution of population in the age/gender strata are likely to vary across the areas. When the needier areas constitute a minority of the population, then a simple age/gender adjustment may "undo" the adjustment for need built into the existing delivery and produce a baseline that is more "regressive" than the existing level of services. Any subsequent adjustment for need would have not only to redress the initial regressive adjustment for age/gender, but would have to take into account the differences in the effect of the need variable across the age/gender strata.

Another problem in calculating need is associated with the distribution of the population in the Province, with its large concentration in Winnipeg. This raises another methodological issue not unrelated to the previous concern. There are serious questions regarding the appropriate way to calculate average utilization patterns. Since allocations are to be made to communities in regions, it seems appropriate to perform calculations which take ecological characteristics of well defined communities into account. That can be done either on a population weighted basis or on the basis of treating the community as the unit of analysis i.e. allowing each community to contribute equally, regardless of population size. While there are arguments for each of these approaches, we conclude that for purposes of regional funding the latter is more appropriate because community level effects are assumed to contribute to need. This orientation results in more significant transfers, especially out of Winnipeg in the case of ambulatory visits.

The stability of socio-economic variables over time and hence their suitability as a basis for needs adjustment are also examined. Although substantial stability is observed, we argue for the use of rolling average values over time as a basis for allocation. We do so for two reasons. First, the Census data upon which the indicators are based contain significant rounding, sampling and perhaps systematic error, and so the use of data from more than one time period mitigates these problems to some extent. Secondly, there is no conclusive evidence that socio-economic factors act decisively on health status over a single time period.

Hence, it is not clear how lower socio-economic status one year ago, versus lower status five years ago affects additional need for health care. Hence, a more longitudinally based set of measures may capture need more closely than a single proximate measure.

The methodology examined in the paper has the disadvantage that it is very data intensive and cannot be easily implemented in other jurisdictions, or other components of health care funding which do not have the data in readily accessible form. Where adequate data is not available to implement this methodology simpler approximations to need may have to serve as proxies. Nevertheless, the methodology developed here identifies strong links between need and allocation across the age/gender strata and utilizes indicators from demographic, health status and socio-economic categories. It is useful for sector specific analyses, especially planning and reallocation, when current allocations are not closely aligned with needs. It has provided useful insights into the development of needs-based funding models in the Province. Moreover, where existing patterns of acute care use are more closely associated with population health needs, (such as in the case of acute care in hospitals) current use may furnish a basis, when combined with the methodology elaborated here, for reallocating other health care resources in a needs-based fashion.

INTRODUCTION

As part of a trend in Canada towards devolution of responsibility to lower levels of administration, a number of the provinces, among them Saskatchewan, British Columbia, Alberta and Quebec, have begun to establish regional authorities to manage the delivery of health care services. The Province of Manitoba has recently established provisions for 12 Regional Health Authorities. One of the first policy challenges engendered by such a move is determining the appropriate level of funding to permit each region to purchase services for its residents.

There is a growing consensus across the country that funding allocations should be based on an appropriate measure of need for health care resources. There is, however, no consensus on what constitutes need or how it might be measured, let alone how it might be implemented as a basis for allocating funding.

The population health literature suggests a broad range of factors associated with a population's need for health care, but three categories predominate: demographic, socio-economic and health status. The number of residents and the mix according to age and gender have long been identified as demographic factors affecting a population's need for health care. Areas with a combination of socio-economic characteristics including high unemployment, low educational levels, high levels of single parent families and poor housing have been found to be at risk and to have high health needs. Finally, areas whose residents are in poor health, typically measured by high premature mortality rates also have an obviously greater call on health care resources.

Using measures such as these to develop estimates of an area's need for health care evokes a number of nettlesome theoretical and practical problems. Here, we suggest some candidate methodologies for deriving measures for allocating health care resources while taking these factors into account. After examining a number of alternatives, we develop, explicate and examine a methodology which was first piloted as the needs-based planning model for physicians in Manitoba. This report makes the methodology more accessible to policy analysts with an eye on the growing demand for the construction of a needs-based allocation mechanisms. One of the advantages of this methodology is its potential for providing a measure of how much additional reallocation should be made among regions for a given increment of need.[1] For example, how many additional visits should be allocated to Region A that has a premature mortality rate that is .1 per thousand greater than the average premature mortality rate in the Province.[2] Below we discuss possible extensions of the methodology to other sectors of expenditure, as well as some of its limitations.

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[1] Technically this is referred to as the coefficient linking a measure of need and the amount of reallocation.

[2] We present a methodology which uses ambulatory visits to physicians as a basis for calculating entitlements. The focus is on explicating a methodology for arriving at preliminary estimates of need across geographic regions. In doing this, certain issues that require further application if one is to move precisely from the existing situation via a measure of visits to a measure of funding requirements are not addressed in depth. Thus such factors as variations in the mix between generalist and specialist visits across regions, and physician workload variations, are not explicitly included in the model. Later, for illustrative purposes, the translation from visits to dollar entitlements is done on a straight line basis where expenditure requirements are presumed to vary linearly with visit needs. Consequently, throughout the paper we refer to need in terms of either visits or funding requirements.

FACTORS POTENTIALLY USEFUL IN DETERMINING NEED FOR HEALTH CARE

Age and Gender

Two of the most common factors associated with need for health care are the age and gender of the population. It is well established that utilization patterns in the population vary as an interactive function of these two variables. It is standard procedure in comparing populations on any number of characteristics to adjust for age and gender differences in populations.

Robert Evans (1988) in a widely circulated but unpublished paper "Squaring the Circle: Reconciling Fee-for-Service with Global Expenditure Control" argued for the use of age and gender adjustment as the fundamental basis for allocating resources for physician care. And while he acknowledges that other measures of need are probably necessary, he notes that they are difficult to identify. The main focus of his paper was on the distribution of expenditures rather than on the number of physicians or physician visits to be allocated to areas. Roughly put, he suggested breaking the population into a fine set of age categories, dividing those into gender categories, and then computing the provincial average expenditure rates on physician services in the categories. Those computed averages could be used to allocate money for the purchase of physician services for each area. "Need" would be defined by the average utilization rate in each category and hence each area's relative need would be defined by its population mix of ages and genders. Each area would get the sum of the average expenditures in each age/gender category times its population in that category. Evans' proposal for an age/gender adjustment represents a sort of smoothing out - giving each area an expected allocation on the basis of its population's age/gender distribution.

We were interested in applying this sort of logic to health care expenditures as a first step in identifying relative need. And, given other potential factors contributing to need, we were interested in possible expansions of his model to include other factors such as those noted above. To demonstrate how this might be done, we began by applying his model to ambulatory visits to physicians.[3]

How, precisely, can we make an adjustment of the sort Evans proposed? We started by identifying all ambulatory visits in the Province outside of hospitals in 1993/94 at the individual level.[4] Starting at the municipality level of aggregation (282 municipalities), we divided the Province into 58 Physician Service Areas. These areas were defined in terms of where individuals were getting the bulk of their visits. The defining characteristic was a concentration of population and an associated set of physicians (usually no fewer than five) serving that population (Roos et al., 1996).

Using visits as the dependent variable, Evans' argument can be easily represented (using suitable assumptions) in the mathematical form commonly known as a multiple linear regression model. A number of models are possible since the choice of age categories is somewhat arbitrary, but we chose to divide the population into 21 age and 2 gender categories: 0-1, 2-4, 5-9, 10-14, ... , 90-94, and 95+; male and female.[5]

The dependent variable was the actual rate of ambulatory visits to physicians and to nursing stations.[6] The units of analysis were the age and gender categories in each area. Thus, each physician area was represented by 42 data points (one for each age and gender category) for a

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[3] The data we use leaves out ambulatory visits to physicians who are salaried since those data are very difficult to capture. Hence most emergency room visits and visits to clinics are not included in the data, but indications are that these do not substantially affect the overall numbers.

[4] A few northern areas receive ambulatory visits at nursing stations which are not attended by physicians. Without attempting to evaluate the relative merits and quality of such visits as compared to physician visits, we have included them as ambulatory visits so that those areas have reasonably comparable data on primary care contacts to those of other areas. Individual level data are not available for those visits, and so they have been allocated to the age/sex strata described below on the basis of average visit levels in those strata in comparable communities.

[5] This procedure is similar to the age/gender adjustment carried out by others as a first approximation to need (see for example Eyles, Birch and Chambers, 1994). Although they do not use regression, their results are comparable to those that would be obtained by this form of regression (except for the weighting by population - see our discussion below.

[6] While the objective of the exercise is , ultimately, to develop a methodology for allocating dollars, given the concentration of specialists in Winnipeg, it was judged more appropriate to base the analysis on visit rates as a way to control, partially, for variations in supply. Some implications of moving from visit rates to dollar allocations are discussed below.

total of 2436 observations. The areas varied in population size from 1,020 to 120,250 and the age and gender groups varied in size from 1 to 6,554.

Some comment is in order on the appropriateness of using physician delivery areas as the geographical level of analysis employed in this study. We have chosen the physician delivery areas as the level of analysis for both statistical[7] and policy relevant reasons. A good policy model should not only accurately represent the relevant factors which it is designed to capture, but should also have other properties. It is important that the model not be subject to unduly large random fluctuations attributable to problems such as sampling. And the model must have enough data points to allow for a meaningful statistical analysis. Moreover, the model should include variables that are acknowledged to be both positively and normatively relevant, and all variables must have an adequate level of reliability. However, the trade-offs the analyst must make between the number of data points and the variability of the data over time are not based on absolutes.

The number of data points must be large enough to support the number of variables in the model. In this case, 12 Regional Health Authorities simply do not furnish enough data points. On the other hand, the statistical fluctuations in factors such as premature mortality at the municipal level may be too great, given the small populations in a number of the municipalities. Physician service areas furnish a mid-level for the analysis which moderates both of those problems. In addition, since the physician areas are built on clusters of physicians which are likely to reflect practice patterns related to the characteristics of the populations in those areas, they are likely to offer a further stability and validity to the model. To the extent those areas more closely reflect moderately homogeneous communities, the ecological variables are more likely to enter in a meaningful way. Furthermore, aggregation from the physician area level to the regional level has been shown to proceed in a relatively

[7] A regression based model requires more areas than can be provided by the Regional Health Authorities. It would be possible to perform estimates with individual level data, but given that the socio-economic data were only available at ecological levels, that path was not followed.

straightforward fashion. For Regional Health Authorities, any allocation can be calculated by summing the allocations of the physician areas within that Region.

To weight or not to weight?

But a major decision had to be made before proceeding with the analysis: how to deal with the varying group/area sizes in the data. One possibility was to do a population weighted analysis to take into consideration the different sizes of the areas under consideration. That would be consistent with Evans' original proposal. Proceeding in that way would give weight to an area's population in determining an average utilization pattern. Hence, the patterns in more populous areas would play a greater role in defining an average pattern than would the patterns of more sparsely populated areas. However, to the extent that there might be other implicit variables (such as physician supply, transportation costs or socio-economic factors) which might be correlated with the size of the population of an area, using a population weighted analysis would also bias the model in the direction of those underlying variables. The resulting "average" pattern would reflect utilization patterns of large population areas more than it would those of smaller areas.[8]

Moreover, in Manitoba, it is plausible that indicators of need might vary inversely with population size across the areas in question. It is also likely that usage patterns across the age/gender strata vary both as a function of population size, socio-economic status and health status. Hence, a population weighted average could underestimate (or overestimate) the need of smaller areas, representing, as it would, the prevailing pattern of delivery in the larger areas. Since we were interested in identifying variables reflecting need, and these variables might be correlated with the population size of an area, we decided against using a population weighted analysis in the first stages. We did, however, perform population weighted analyses to check for these hypothesized underlying relationships between population size

[8] To clarify the implications of using a population weighting, one could imagine the results were the United Nations to attempt the identification of links between the socio-economic characteristics of nations and their health statuses by using a population weighted model. China and India would largely determine the result, and the effects of industrialization captured in the European and North American countries of smaller populations would be largely masked.

and other relevant variables. Throughout the first part of the discussion, we will, therefore, provide comparative statistics from weighted analyses in footnotes.

One aspect of using an unweighted regression analysis to calculate relative need for ambulatory visits requires comment and clarification. Using an unweighted regression to calculate average utilization patterns does not mean that in calculating an area's allocation of visits, population size should be completely ignored. What it means is that in estimating the parameters defining utilization, i.e. in estimating the relationship between age/gender and utilization, each physician service area is treated as an entity and as an equal and unique contributor to the estimation of the parameters.[9] Thus, for example, the allocation to 0 - 1 year old male babies was calculated looking at how this age stratum uses services across the 58 physician areas. The usage pattern of these babies in Winnipeg North East, Cross Lake, Melita, etc. were all given equal weight in calculating the average allocation to the stratum. For each area, the allocation of visits for young male babies was subsequently calculated by taking the resultant average utilization rate and multiplying it by the number of such babies in the area. Thus, the size of the population did not enter into the calculation of the average rate of visits, but entered directly in the calculation of each area's allocation of visits. Accordingly, the age/gender subpopulations of areas were the fundamental units of analysis, and each subpopulation in each area was treated as having equal weight in the analysis.[10]

The multiple linear regression analysis is really nothing more than a kind of averaging of utilization patterns of ambulatory visits according to the areas' age and gender groupings. The coefficient of each of the input variables in the regression represents the weight that is accorded to that characteristic's impact on utilization. It gives a weight to each category (to repeat our previous example: how many visits, on average, a 0 - 1 male infant gets in the Province). The overall goodness of fit of the model shows the extent to which the areas in the Province are receiving average levels of ambulatory visits in terms of their age/gender

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[9] This means that the definition of the physician service areas defines the implicit weightings in the model.
[10] This methodological choice is not without risks of its own. Assigning each community equal weight allows very small communities the same impact on the definition of average utilization patterns as very large communities.

characteristics, or put another way, the extent to which differences in age/gender composition explain differences in utilization among areas. The model is a purely descriptive construct. One can use the model to calculate what the average expected ambulatory visit level would be for each area based solely on the age/gender characteristics of the area.[11]

The model to be estimated is:

Visits per capita = F(age1,...,age21, gender, (age1,...,age21)*gender)

The regression analysis provides parameters for the equation describing the average utilization patterns associated with the different age and gender categories. It captures the relationship between ambulatory care visit levels and the various age categories, differences in gender and also the well known differences in utilization patterns of men and women as a function of age (the starred (*) or interaction terms).

The overall fit of the model is highly significant ($F=32.39$, $p<.0001$). The model had an adjusted explained variance of 36%. In simple terms, 36% of the differences in ambulatory visits to physicians across the 58 areas can be accounted for by differences in the age/gender population composition of the areas. Table 1 contains the analysis of variance data from that regression model.[12]

[11] Below we will present other models which average according to age, gender and other variables.

[12] Due to the greater relative uniformity of utilization within the most populous physician delivery areas a population weighted regression explains much more of the variance. The population size enters into the calculation of the variance, and the uniformity noted picks up that contribution. Hence, 74.7% of the variance is explained, and the regression has a high F value statistic of 170.29 significant at the .0001 level. However, the weighted model has a statistically inferior model fit in that it is biased towards the patterns of the more populous areas as is evidenced by the fact that the smaller areas are outliers in the regression.

Table 1: Model of Ambulatory Visits vs. Age and Gender with Interactions

Source	DF	Type III SS	Mean Square	F Value	Pr > F
AGEGROUP	20	14474.71	723.73	58.92	0.0001
GENDER	1	736.11	736.11	59.92	0.0001
AGEGROUP*GENDER	20	1053.18	52.65	4.29	0.0001

Thus there is a strong relationship between the age/gender characteristics of an area and their utilization of ambulatory visits. On first glance, the formula would appear to provide a reasonable basis for allocating physician visits. If we wished to use the model as a normative tool or formula, we would give each area an average allocation by multiplying the coefficient of each age, gender and age/gender category by the population size of that category in the area and summing these over the categories. Then, the average expected visit level per capita would be calculated for that area by dividing the calculated sum by the population of the area.

But before proceeding in this way, we need to be clear as to how the results of this analysis should be interpreted as a guide to policy. The regression equation is a tool which simply calculates the average relationship between age and gender and actual ambulatory visits in the Province. The regression describes what "is" on average, given the assumptions of the regression model. Using the results as an allocation formula would give each area visits according to its age/gender characteristics based on the existing average pattern of usage in the Province. One would be smoothing out anomalies in average visit rates across the Province attributable to differences in age/gender specific visit rates. It would be appropriate to use the results in this way, normatively, as a basis for allocating ambulatory visits to the areas, only if certain conditions obtained. An allocation based only on an age/gender adjustment might be justified if we had reason to believe that, for the Province as a whole, on average, according to age/gender characteristics, physician visits are already appropriately distributed. Making that assumption without justification would be a classic jump from the "is" (albeit on average) to the "ought". It would require the assumption that, on average, current allocations across the age/gender strata capture need adequately. That clearly is a large assumption, and before making that leap, it is only prudent to run some independent tests of the assumption. Can one justify that assumption? And if so, how?

An appropriate relationship with premature mortality

It has been argued convincingly that premature mortality, specifically mortality that occurs prior to age 74 (0-74 years) is a good single measure of a population's need for health care services (Birch, Eyles and Newbold, 1995, Birch and Eyles, 1991).[13] Put in common parlance, it is intuitively clear that dying young is an indication of poor health. If the age/gender adjusted area allocation calculated from the model is to have any claim to validity as a policy prescription, it should show an appropriate relationship with this alternative indicator of need. If we are treating physician visits as a health care resource to be distributed in accordance with measures of need, then one would want an area's allocation of visits, as determined by the model, to be positively and significantly related to the premature mortality rate of its population. What that means is that the areas in which more people on average die younger can be thought of as areas of high health needs, and should be allocated more ambulatory visits.

As noted above, the calculation of an area's allocation of visits based on its average age/gender characteristics is a relatively straightforward process once the regression equation has been specified. The population of the area in each age/gender category is used and the coefficients from the regression are multiplied by the relevant population numbers. These are summed to get a total allocation of visits. Thus, for example, if on average in the Province, girls between the ages of five to nine received 3 visits per year, and an area had 100 girls of that age, then that component of the population would generate a total allocation of 300 visits. This calculation would be done for each age/gender stratum for the area and the total

[13] Initially, premature mortality was defined as the Standardized Mortality Rate of individuals between birth and 64 years of age. The accepted standard appears to be moving towards the use of the ages from 0 to 74 years and, here, we adopt this operationalization.

allocation would be added up. The total visits are then divided by the total population of the area to generate a per/capita allocation of visits for the area.

We tested for the relationship between this per capita allocation and the premature mortality rate across the physician service areas. When we compared areas' age/gender adjusted allocation of visits with their age/gender adjusted premature mortality rates, we found the relationship to have a Pearson correlation coefficient of -.373 (p=.004).[14]

But note the negative sign of the statistic indicates a direction to the relationship. What does that negative sign mean? Simply put, it means that using the formula derived from this approach would give areas with lower premature mortality rates (and presumably better health status) more visits per capita and areas of higher mortality (reflective of worse health) fewer visits. This prevailing pattern of usage is regressive relative to premature mortality. What might account for this? Since the regression and the measure of premature mortality are both "age/gender adjusted" this relationship cannot be simply due to the fact that areas of high premature mortality have younger populations which use fewer visits. Instead, it is likely that there are other reasons for this negative relationship. The answer may lie in other factors which are also closely related to existing patterns of primary care visits. Perhaps there are differences across areas attributable to physician supply, or ease of access, or differences in practice patterns associated with urban areas, or even differences in utilization patterns across the age/gender strata as a function of socio-economic or health status factors. Such relationships could possibly explain why areas with higher premature mortality are actually using fewer visits than their age/gender composition warrants. But whatever factors might explain this discrepancy, using only a simple "age/gender" adjusted average as a basis for reallocation would be regressive relative to a credible measure of need if one makes the assumption that levels of physician services should be directly related to a population's health status (rather than to other factors).

[14] The corresponding relationship from the population weighted regression is -.347, (p=.008).

This possibility casts a significant shadow over Evans' proposal. It renders the simple age/gender adjusted allocation questionable, and even perverse, as a sole measure of need, at least in Manitoba.[15] Since the allocation from the analysis is negatively related to a credible measure of need, we argue that it may be inappropriate to use the existing age/gender adjusted pattern of usage as a norm towards which to adjust. Further examination of possible adjustments for need is, therefore, required.

We can take a somewhat closer look at why an age/gender adjustment alone leads to the problematic prescription described above, that is, a reallocation which yields a negative relationship between premature mortality and age/gender adjusted average physician visits. Simply put, this means that the areas of poorer health status (as measured by premature mortality) get, on average, fewer visits.

Since both the visit levels and premature mortality are adjusted for age and gender, this negative relationship cannot be explained by the fact that, generally, the worse off areas have younger populations which utilize fewer visits. Rather, it may be that the patterns of use across the age/gender strata differ as one moves from areas of poorer to better health. Thus, for example, suppose poorer areas tend to use more visits in the earlier years of life than do better off areas. If the poorest areas constitute a minority of the areas, then the regression will allocate visits to the young strata of the population according to average (majority) usage in those strata and specify a lower visit rate for younger segments of the population and a higher visit rate for older segments than are utilized in the poorest areas. Since the poorest areas are generally younger, the visit levels allocated to them by the regression will be below their current utilization levels and could be negatively correlated with premature mortality.

Poorer areas' existing use of visits may be reflective of their need as measured by premature mortality.[16] However, the reallocation of visits away from current usage according to the age/gender adjustment may reduce their average visit rates enough so that their newly

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[15] Manitoba may be somewhat unique in this regard inasmuch as it has a number of small population centres whose residents tend to be young, of poor health status and with high health care needs.
[16] This tendency would be aggravated if a population weighted analysis were used as the basis of the regression.

calculated average allocation may be negatively correlated with premature mortality. In this way, the differences in existing visit rates in the age/gender strata as a function of socio-economic status in combination with differences in the population distribution across the age spectra as a function of socio-economic status might explain the negative relationship identified. Any subsequent attempt to adjust for socio-economic status from the initial age/gender adjustment would have to counteract these complex "interaction" effects between age/gender characteristics and socio-economic status.

These observations, coupled with our problematic result, give us reservations about using a simple age/gender adjustment as a sole definition of need. These reservations even act as a caution regarding the use of age/gender adjustments as a first stage estimation of need in a process which later adjusts for need. If there are indicators of need which are correlated with the demographic characteristics of areas, then what may appear to be a "neutral" first stage adjustment for the age/gender characteristics of regions may cast needier regions in an unfavorable light. In other words, an age/gender adjustment is not necessarily a neutral adjustment as a basis for calculating need. Any subsequent adjustments for need from an age/gender adjusted base, would reallocate from a "baseline" which was lower than actual usage. A second stage adjustment for need would consequently appear larger than would an adjustment from current usage.

Thus, Evans' seemingly commonsensical prescription (or at least the first stage of it) leads, in Manitoba, to a potentially problematic result. Moreover, we think it should give pause to those who would use only age/gender adjustments elsewhere.

There are a number of ways of coping with this troublesome relationship between the age/gender characteristics of the populations and ambulatory visits. One obvious step is to build a model which explicitly takes into account not only age/gender characteristics, but also an explicit measure of need so that the adjustment to the average is made in accordance with both age/gender characteristics, the identified need indicator and interactions of that need indicator with the age/gender strata. A number of possibilities present themselves as candidates. One alternative is to include a measure of premature mortality in a model to get an average ambulatory visit level taking age/gender and premature mortality into account explicitly. Another is to include a measure of socio-economic status in the model as a factor indicative of need. A third alternative is to include all of these variables: age/gender, premature mortality and socio-economic status in a model to account for differences in visit patterns.

We pursue and compare these three approaches below. And in each case we use a regression technique which allows for "interactions" of the sort alluded to above to take into account the possibly interactive patterns of use between age gender strata and other measures of need. It should be noted that all of these approaches have large data requirements. But one of the main purposes of this paper is to examine the potential benefits of using a sophisticated methodology based on a large database and to see what differences these various approaches make.

Age/Gender and Premature Mortality

Including premature mortality as an additional predictor for ambulatory visit rates yields the following model:

Visits per capita = F(age1--age21), gender, Premature mortality,

This model generates an equation which represents the average ambulatory visit rate per physician area, taking into account not only age and gender, but also premature mortality. Also included in the equation are terms such as "gender*premature mortality". That term is a so-called "interaction term" which takes into account the fact that visit rates in different gender categories may differ for areas with different premature mortality rates. For example, if higher premature mortality rates affect the visit rates of men in the Province in a different way than they do those of women, the interaction term, "Gender*Premature Mortality", in the regression, will capture the strength of that effect. When this relationship is taken into account, an allocation of visits to the different physician areas will add a correction factor for this interactive effect of the two variables. The other interaction terms (those with "*'s" in them) capture the more complex relationships between other characteristics of the population and their use of visits.

When the regression equation relating visits to age/gender and premature mortality is assessed, the results show a significant relationship between age/gender, premature mortality and visit levels. The model explains 39.9% of the variance in visits (F-value = 18.51, $p<.0001$). This is slightly more than the 36% explained by age and gender alone in the previous model. And not surprisingly, (since premature mortality was a component of the model) when the per capita allocations of ambulatory visits are calculated on the basis of this equation (as described above in the previous section) and then regressed against premature mortality, the correlation was positive and strong: ($r = .84$, $p = .0001$).[17] Thus, calculating area allocations on this basis would not suffer from the same problem as would adjusting on the basis of only age and gender since its average allocation of visits would correlate with a well accepted measure of need.

Table 2: Model of Ambulatory Visits vs. Age, Gender and Premature Mortality with Interactions

Source	DF	Type III SS	Mean Square	F Value	Pr > F
AGEGROUP	20	850.28	42.51	3.62	0.0001
GENDER	1	3.16	3.16	0.27	0.6038
AGEGROUP*GENDER	20	177.95	8.89	0.76	0.7678
MORTALITY	1	1144.60	1144.60	97.37	0.0001
MORTALITY*AGEGROUP	20	241.97	12.09	1.03	0.4226
MORTALITY*GENDER	1	21.39	21.39	1.82	0.1775
MORTALITY*AGEGROUP *GENDER	20	307.79	15.38	1.31	0.1613

[17] While there are similarities between this allocation and that which would be achieved by the procedure proposed by Eyles et al. (1991) there are significant differences. The model developed here does not use a population weighted average age/gender indirect adjustment as a baseline as they do. Moreover, the full regression model takes into account interaction effects of age/gender categories and premature mortality as they affect resource requirements.

However, ideally, to act as a model for reallocation, the equation should satisfy some other desiderata. Specifically, the equation should not be biased. An analysis of the residuals shows that a number of the areas are outliers, indicating that the estimation is biased against them. Moreover, for a model to be plausible, one would expect most of the terms entered into the equation should be statistically significant predictors of utilization. An analysis of variance based on this equation shows that premature mortality enters into the analysis in an overpowering way, and except for a main effect of age, the model virtually eliminates all interaction effects.[18] (See Table 2). While the introduction of premature mortality into the model orients the allocations in the proper direction, it seems to mask the effects of all other variables save age. As such, it appears not to capture any interaction effects of population characteristics on utilization. Moreover, although the model explains a bit more of the variance it is, as a whole, because of its additional terms, less significant than the age/gender model, as evidenced by its lower F-statistic (18.51 vs. 32.39). Thus, before opting for this model as a basis for reallocation, we need to compare its results with those that might be obtained from other models.[19]

Age/Gender and Socio-economic Risk

One of the most deeply researched and well authenticated relationships in the population health literature is between what has been described as socio-economic status (or relative deprivation) and health status. An earlier report from the Manitoba Centre for Health Policy and Evaluation and a subsequent article report an index of socio-economic factors (SERI) which appear to be closely related to health status and health care resource utilization (Frohlich and Mustard, 1994; Frohlich and Mustard, 1996). The index uses socio-economic

[18] To anticipate results, we can note that it is possible to use a reduced model with age/gender and Premature Mortality without all of the interaction terms, but as will be seen below, the age/gender/SERI model has a whole range of more desirable statistical and face validity characteristics.

[19] The population weighted model explains 79.6% of the variance (F=109.14, p=0.0001) and average entitlement is also highly correlated with premature mortality r=.783, p=.0001.

characteristics captured in the aggregate Census data. Details of the development can be found in the works cited.[20]

Six variables in the Census data were identified as highly descriptive of the socio-economic status of population aggregates as they relate to health status and utilization of health care resources in Manitoba. They are:

- the percentage of the labour force unemployed: ages 15 to 24,
- the percentage of the labour force unemployed: ages 45 and 54,
- the percentage of single parent female households,
- the percentage of the population between the ages of 25 and 34 having graduated high school,
- the percentage of females participating in the labour force and
- the average dwelling value.

Those variables were combined into an Index, SERI, as described in the works cited and as sketched in Appendix B. This index can be used in combination with the age/gender categories used above in an alternative attempt to build an equation representing a justifiable set of allocations of ambulatory physician visits. The equation to be estimated is comparable to the previous equation using premature mortality, with SERI scores being substituted for premature mortality rates.

The equation to be estimated is as follows:

Visits per capita= F(age1--age21), gender, SERI,
(age1--age21)*gender, (age1--age21)*SERI,
gender*SERI, (age1--age21)*gender*SERI)

The overall fit of this equation is substantially better than that of both previous models. Over 65.7% of the variance is explained by the model ($F=53.48$, $p<.0001$) versus 39.9% by the age/gender/premature mortality model. Moreover, the analysis of variance appears to be well balanced in that all factors in the equation are significant. (See Table 3). Socio-economic

[20] Appendix B contains a brief discussion if the index SERI and some details of its derivation which may be useful as background for understanding why we believe it is useful to include measures of socio-economic status in calculating allocation of health care resources

factors are clearly and strongly related to use patterns, and the effect varies over the different age/gender categories. The significance of the interaction terms indicates that the equation describes the interactions of socio-economic factors and age/gender characteristics on utilization patterns. Moreover, the equation is statistically unbiased.

Table 3: Model of Ambulatory Visits vs. Age, Gender and SERI with Interactions

Source	DF	Type III SS	Mean Square	F Value	Pr > F
AGEGROUP	20	14512.33	725.61	108.24	0.0001
GENDER	1	731.99	731.99	109.19	0.0001
AGEGROUP*GENDER	20	1035.95	51.79	7.73	0.0001
SERI	1	7879.72	7879.72	1175.45	0.0001
SERI*AGEGROUP	20	2520.84	126.04	18.80	0.0001
SERI*GENDER	1	176.34	176.34	26.31	0.0001
SERI*AGEGROUP *GENDER	20	2148.40	107.42	16.02	0.0001

Again, we can test to see whether the per capita allocations under this model are positively related to premature mortality. Calculating the per capita allocations based on the regression as described above, we can test to see whether areas of higher premature mortality generally get a larger allocation of visits under this formula than areas of lower mortality.

The relationship of premature mortality to per capita allocations was highly significant (Pearson correlation = .500, p<.0001). Moreover, the relationship between the per capita allocation to the areas and the premature mortality of the areas is in the appropriate direction. The greater the premature mortality, the greater the per capita allocation of visits. This, in our opinion, presents a more promising model for reallocation, but despite the positive and promising results of the combined age/gender/SERI model, the possibility remains that a model combining all three factors might do even better.[21]

Age/Gender, Socio-economic Risk and Premature Mortality

A fourth model to identify possible expected levels of ambulatory visits can be constructed by combining all the factors we have examined to date. Such a combined model would have the following form:

Visits per capita = F(age1--age21), gender, Premature mortality, SERI,
(age1--age21)*gender, (age1--age21)*Premature mortality,
(age1--age21)*SERI, gender*Premature mortality,
gender*SERI, Premature mortality*SERI,
(age1--age21)*gender*Premature mortality, (age1--age21)*gender*SERI,
(age1--age21)*Premature mortality*SERI,
gender*Premature mortality*SERI,
(age1--age21)*gender*Premature mortality*SERI)

This model doubles the number of variables used to explain physician visits, however, it generates only a modest improvement in explained variance: 69.6% ($F=30.60$, $p<.0001$) and many of the interactions included are not significant. The residuals of the regression also show an unacceptable pattern indicative of bias, with a number of the observations being outliers in the regression. The analysis of variance (See Table 4) shows that a number of the terms are significant contributors to the explained variance. However, the addition of premature mortality contributes relatively little explanatory power (less than 4%), does not enter significantly in any of the interaction terms, and dilutes some of the interaction effects evident in the age/gender/ SERI equation. Moreover, the expanded model reduces the size of the F statistic, indicating that the larger model is more likely to have been due to chance than

[21] A population weighed result yields an analysis of variance which explains 81.4% of the variance, and has an F-statistic of 122.33 significant at the .0001 level. But this greater amount of explained variance is obtained at some cost. Two of the interaction terms significant in the unweighted age/sex/SERI model, and which one might expect to have explanatory power, are not longer significant. Moreover, the relationship between areas' calculated entitlements and premature mortality is not as strong as with the unweighted model: $r=.417$, $p=.0011$, vs $r=.5$, $p=.0001$. Our interpretation of this is that the weighting by population dilutes the relationship between the socio-economic variables and entitlements because of the large size of the Winnipeg populations and presumably because there is a weaker relationship between the use of ambulatory visits across the city's various areas and measures of need.

was the age/gender/SERI model.[22] This, coupled with the fact that the new variable and its seven interaction terms add only 4% explained variance to the model, lead us to conclude that its introduction does not adequately compensate for its increased complication and its associated dilution of interaction effects. Since these effects are ones which one might anticipate theoretically and appear in the age/gender/SERI model, their absence in this model is a further reason to prefer the age/gender/ SERI model. Moreover, when area allocations are computed and their relationship to premature mortality is computed, the Pearson correlation is .388 (p= .0026), a weaker relationship than is obtained from the previous model.[23]

[22] Although both models are statistically significant, and descriptive of an underlying relationship, the fact that one is less so would lead on the believe that it is less likely to reflect an underlying causal relationship than the more significant model. The age/gender/Premature Mortality model may get its power via its correlation with the more powerful underlying variables (as captured in SERI) in the age/gender/SERI model.

[23] The population weighted model explains 83.4% of the variance (F=67.41, p=0.0001) and average entitlement is also highly correlated with premature mortality r=.513, p=.0001. But as in the unweighted case, the added complexity reduces the F-statistic and the Pearson's r. And, as argued above, there are theoretical reasons for not adopting a population weighted model.

Table 4: Model of Ambulatory Visits vs. Age, Gender, Premature Mortality and SERI with Interactions

Source	DF	Type III SS	Mean Square	F Value	Pr > F
AGEGROUP	20	2093.34	104.66	16.97	0.0001
GENDER	1	82.95	82.95	13.45	0.0003
AGEGROUP*GENDER	20	689.00	34.45	5.59	0.0001
SERI	1	152.03	152.03	24.65	0.0001
SERI*AGEGROUP	20	191.66	9.58	1.55	0.0554
SERI*GENDER	1	0.05	0.05	0.01	0.9217
SERI*AGEGROUP*GENDER	20	322.75	16.13	2.62	0.0001
MORTALITY	1	284.04	284.04	46.05	0.0001
MORTALITY*AGEGROUP	20	602.33	30.11	4.88	0.0001
MORTALITY*GENDER	1	15.79	15.79	2.56	0.1097
MORTALITY*AGEGROUP *GENDER	20	611.74	30.58	4.96	0.0001
SERI*MORTALITY	1	18.92	18.92	3.07	0.0800
SERI*MORTALITY*AGEGROUP	20	81.74	4.08	0.66	0.8657
SERI*MORTALITY*GENDER	1	13.77	13.77	2.23	0.1352
SERI*MORTALITY*AGEGROUP *GENDER	20	161.55	8.07	1.31	0.1611

We would argue that the simpler age/gender/SERI model produces a better fit than the age/gender/SERI/premature mortality model while preserving a stronger and more appropriate positive relationship with premature mortality. Moreover, the existence of significant interaction terms in the age/gender/SERI model indicates that SERI is capturing a variety of the interactions among differences in utilization due to age and gender which one might expect to be present in utilization patterns. The premature mortality model does not capture differences in utilization patterns within age/gender strata attributable to differences in health status. On balance, therefore, we judge the age/gender/SERI model most appropriate for establishing an average utilization rate for the Province. Table 5 summarizes the quantitative results of the four models, both unweighted and weighted by population. Table 6 summarizes the qualitative criteria we have invoked in our arguments regarding the unweighted models, namely the existence of a positive relationship between the model and premature mortality, the bias of the residuals and the number of terms in the model that enter significantly. Taken together they convey a sense of why the age/gender SERI model was selected.

Table 5: Comparison of Models of Ambulatory Visits on a Community and Population Weighted Basis

Model	Unweighted				Weighted			
	r^2	F	p	β	r^2	F	p	β
AGEGROUP*GENDER	.360	37.39	.0001	-0.129	.747	170.29	.0001	-0.093
AGEGROUP*GENDER *MORTALITY	.399	18.51	.0001	0.570	.796	109.14	.0001	0.323
AGEGROUP*GENDER *SERI	.657	53.48	.0001	0.643	.814	122.33	.0001	0.257
AGEGROUP*GENDER *MORTALITY*SERI	.696	30.60	.0001	0.493	.834	67.41	.0001	0.391

Table 6: Qualitative Aspects of Models for Needs-Based Allocations

Model	Correlation With Premature Mortality	Unbiased Estimations (Acceptable Residuals)	Terms Enter
AGE*GENDER	Negative	Biased	All Three
AGE*GENDER*PREMATURE MORTALITY	Positive	Biased	Two of Seven
AGE*GENDER*SERI	Positive	Unbiased	All Five
AGE*GENDER*SERI *PREMATURE MORTALITY	Positive	Biased	Eight of Fifteen

Adjustments for Remaining Differences in Premature Mortality

Over the Province as a whole, the regression analysis has demonstrated that there is a relationship between utilization of visits and age, gender, and SERI. Average allocations of visits calculated on the basis of these variables are positively correlated with another established measure of need: premature mortality. We, therefore, feel justified in the assumption that assigning each area an allocation defined by these relationships moves the per capita allocation in the appropriate direction. Giving each area the Provincial average level of visits, adjusting for age, gender and SERI is a step towards developing a method for allocation of physician visits on the basis of need.

But is this smoothing a strong enough reallocative criterion? Recall that the level of correlation between premature mortality - an established need measure - and the new allocation was only .500. Figure 1 presents a plot of the first stage calculated per capita allocation of visits vs. premature mortality.

If allocations were to match premature mortality rates perfectly then all of the points in the figure would fall on the regression line illustrated in the figure. That is clearly not the case. Almost all points fall either above or below the line. Many of the physician delivery areas have allocations which are either above and below what would be an "average" line. Reallocating on the basis of age, gender and SERI according to the prevailing pattern of physician visits accounts for only 25% of the variance in premature mortality. As noted above, premature mortality is one of the leading candidate variables for inclusion in calculations of allocations of health care resources. This relatively loose relationship between the allocation according to the model and premature mortality would seem to imply that the reallocation may not be taking this variable into account adequately. But we have also previously noted that placing premature mortality along with all interactions directly in the model does not improve the relationship between entitled level of visits and premature mortality. The average existing pattern of utilization of visits, while correlating significantly with premature mortality, leaves much variation unexplained. So, using the existing average pattern of usage (adjusted for age, gender and SERI) as the only, and final, basis for calculating allocations is not necessarily appropriate.

While populations in poor health would seem to have the strongest claim to physician services, it does not necessarily follow that providing them with more of these services will "buy" them better health.[24] However, in a capped funding environment, shifting physician resources from areas of relative surplus to areas of relative deficit would seem to be a rational basis for allocation. That conclusion is based on the principle that those in poorer health should be provided more physician visits and resources than those in better health (other things being equal).[25]

We, therefore, decided to introduce a second stage adjustment based on premature mortality to link health status and resource allocations even more closely than in the first stage reallocation. This involved introducing an additional assumption under which to allocate additional visits: the higher the premature mortality, the greater should be the allocation of ambulatory visits. The desirability of doing this is underlined by the obvious and pronounced differences in premature mortality across the physician service areas. Under the assumption of a resource constraint, we assumed that areas with higher than average premature mortality should be given additional allocations, while areas with lower than average premature mortality should have theirs reduced.

The question is "How exactly can one give more weight to premature mortality with an additional adjustment?" How many additional visits on average should be allocated to an area for any given difference in the premature mortality rate? In Britain, the Resource Allocation Working Party between 1977/78 and 1989/90 used a coefficient of 1 to adjust needs according to standardized mortality ratios. Standard deviations in mortality ratio were

[24] It is also possible to hope to increase the health status of the population as a whole by either judiciously reallocating funds within the health care system or, more probably, by shifting resources towards factors that antecedently influence health status.

[25] Contra this argument, if the marginal effectiveness of health care resources were shown to be higher in areas of better health than in areas of poorer health then shifting resources to poorer populations could result in a net reduction in overall health status. But we are not aware of any studies that have established this sort of relationship.

matched by standard deviations in dollar allocations. Subsequently, the adjustment factor was changed to .5 and premature mortality was used as the measure of need. (Mays, Chinn and Ho, 1992).[26] There are few other guides in the literature to tell us what the size should be of the coefficient linking additional need for visits to differences in premature mortality rates. In other words, should an additional standard deviation above the average in premature mortality earn a standard deviation of increased visits (a coefficient of one) or should the coefficient be 1/2 or 2, or whatever?

Our analysis provides, as illustrated in Figure 1, a relationship between allocation of average visits to areas according to our first stage model and the premature mortality rates in the areas. We can use the slope of the linear relationship between an area's age/gender/SERI allocated rates as calculated from the first stage regression and it's premature mortality rate as a basis for reallocation to areas with higher premature mortality rates and away from areas with lower rates. The relationship in the regression equation between premature mortality rate and each area's average allocation as calculated from the first regression was: Allocation= 2.47 + .643*(premature mortality). That equation is represented as the line in Figure 1. As noted above, the relationship explained 25% of the variance and was significant ($F = 18.70$, $p<.0001$). To achieve a second stage reallocation to take into account remaining differences in premature mortality, we subtracted the Provincial average premature mortality rate, 3.58, from the premature mortality rate of each area.[27] That result was multiplied by the slope of the linear relationship (.643) to give an additional adjustment for each area. This adjustment was then added to (subtracted from) each area's allocations as calculated in the first stage regression. Thus, the greater the difference between an area's premature mortality rate and the Provincial mean rate, the greater the adjustment. Those with higher than average premature mortality were allocated additional allocations, those below had their allocation

[26] The allocations calculated by the Resource Allocation Working party were more closely related to what we have referred to as our first stage adjustment.
[27] Here the Provincial mean uses the overall weighted mean for the province.

reduced. Using the slope of .643 allowed us to use a parameter that was derived from the data to do the adjustment. The newly calculated average allocations are represented in Figure 2.

We can check for the relationship between these new allocations and the premature mortality rate. Since, the additional adjustment was based on premature mortality rates, we have built in a relationship between the adjusted allocation and premature mortality. Hence, the relationship is highly significant (Pearson correlation coefficient = .756, $p < .0001$) vs. .500 $p < .001$) for the relationship between the first stage allocation and premature mortality).

Note how the line representing the relationship between the two variables is steeper in Figure 2 than it is in Figure 1. This reflects the additional weight the second stage adjustment gives to premature mortality. Comparing this allocation to the first stage estimation results shows the effects of that additional adjustment. The second stage adjustment corresponds to rotating the data around the middle of the initial regression line in Figure 1 (the average per capita visit level). One can appreciate this by noticing what the effect of the second stage adjustment is on different categories of areas allocations. An area at the Provincial average premature mortality rate would not receive an additional adjustment in the second stage and would receive the same allocation of visits per capita. It would be a fixed point - the same in both figures. An area of higher than average premature mortality would receive more visits and so would be elevated in Figure 2 relative to Figure 1. By contrast, an area with lower than average premature mortality would receive fewer visits per capita. The result is the rotation about the mean premature mortality rate. This adjustment does not change the serial order of the areas' allocated visits, but it does tighten the relationship between allocation of visits and premature mortality, building that component in as an additional normative factor, as discussed above. The new regression of second stage allocation against premature mortality builds in a stronger relationship between allocation of ambulatory visits and premature mortality. This compensates for the relatively loose relationship between per capita visits and premature mortality identified in the first stage allocation.

Moving from Physician Areas to Regional Health Authorities and a Hypothetical Translation of Visits into Dollars

The analysis we have reported above has taken place at the level of 58 physician delivery areas. That level of analysis was chosen because 12 Regional Health Authorities do not provide enough power to perform credible statistical analyses of the sort we have been dealing with. Moreover, we have been using ecological measures which hopefully reflect aspects of communities related to poor health. Although funding of physicians does not fall within the initial mandates of Regional Health Authorities, the Regional level is the level at which other allocations are to occur and it is important to see how this methodology might play out at the Regional level. To facilitate a translation of results to the Regional level, the physician areas were chosen so that each was within a given Regional Authority.[28] Thus, it is a straightforward matter to calculate a Region's allocation of ambulatory visits. A region's allocation can be treated as the sum of the allocations of the component physician areas within the region.[29]

As noted earlier, (See footnote 2) there are a number of issues that need to be taken into account in moving from a calculation of allocating visits to allocating dollars. The visit allocations could be translated into dollar allocations in a variety of ways. The simplest is to calculate the total Provincial expenditure on ambulatory visits in a year and divide that by the number of visits in that year to get an average expenditure per visit. Then each area could be allocated an amount consisting of its allocation of visits times the average expenditure per

[28] It should be noted that, ideally, each physician area should be as homogeneous as possible in terms of socio-economic characteristics in order to maximize the explanatory force of the ecological socio-economic variables. Some trade-off in heterogeneity is made by choosing the areas on the basis of physician practice areas and trimming a very few of these to be contained within Regions. But the relative significance of the SERI variable in the regressions seem to indicate that the trade-off has not been terribly costly.
[29] This actually requires the assumption that the needs of the separate populations of the physician areas are additive (i.e. that their combination under a single funding entity does not introduce new effects which impact on need). We have no reason to question that assumption.

visit. Were this calculation to be done on the basis of the model developed above using this simplifying assumption, the result would be a significant reallocation of visits from the Winnipeg area to most of the other areas, but particularly to the northern remote areas. (See Table 7)

Table 7: Predicted Visits by Regional Health Authority

Regional Authority	actual visits/res	age | gender | seri visits/res	weighted visits/res
Central	4.056	4.715	4.835
North Eastman	5.199	4.892	4.865
South Eastman	3.902	4.458	4.640
Interlake	4.533	5.576	5.149
Norman	4.801	6.966	5.558
Parkland	4.613	6.377	5.571
Burntwood	6.609	7.242	5.668
Churchill[30]	1.072	5.881	5.030
Brandon	4.883	4.561	4.800
Marquette	4.820	5.464	5.247
South Westman	4.314	4.965	5.073
Winnipeg	5.106	4.565	4.788
Province	4.917	4.917	4.917

But a caution is in order regarding this seemingly simple formula. The mix of providers of ambulatory care is different in the different regions. Winnipeg has a much higher proportion of ambulatory visits delivered by specialists such as paediatricians and internists, and their charges are somewhat higher on a per-visit basis. Consequently, allocating money to regions based on an average Provincial expenditure per visit would shift additional resources out of Winnipeg. A serious policy issue would need to be addressed as to whether this additional reallocation is justifiable and, indeed, feasible. This approach raises the difficulty associated with the relatively high concentration of specialists in the urban areas and the potential

[30] There are some questions about the reliability of the visits data from Churchill.

dislocations which could occur if money were reallocated on an average cost per visit basis. This is a limitation of the current approach and raises a further caution regarding extending this analysis in a straightforward way to physician services that do not constitute ambulatory visits. One possible way of generating dollar reallocations from this analysis is to compute an actual current average cost per visit in each of the regions. This would reflect the mix of visits to generalists and specialists in each region. Money could then be reallocated by giving current dollar weighted physician visit allocations to the regions. Doing so would build in a bias towards the existing balance of service delivery, which is weighted towards specialists in the urban areas.

Table 8 presents the results of projecting Regional Health Authority allocations for all physician services (not just ambulatory visits) using the methodology we have outlined above for per capita visit allocations and assigning equal dollar values to all visits. Although making this projection requires yet another set of simplifying assumptions, it is presented here for illustrative purposes. Budgeted figures for 1996/97 are used, and the allocations for both population weighted and unweighted models are presented. From the table, it is clear that the model proposed here would reallocate more than would a regression model weighted by population. The main differences are in the extent to which Winnipeg and Brandon have resources shifted to other areas. Winnipeg would lose roughly 16.4% and 12.4% of its current budget under the unweighted regression and the weighed regression models respectively. The corresponding losses for Brandon are 9.5% and 0% of its current budget. There are also significant differences in the gainers of the reallocated dollars. The reallocation based on the unweighted regression model gives almost all of the additional reallocation away from Winnipeg to the northern Regional Health Authorities.

Table 8: Allocation of 96/97 Dollars ($1000s) for All Medical Services Unadjusted for Fee Differential[31]

	Actual dollars	Mustard allocated dollars	Regression age | gender | seri dollars	Regression (weighted) dollars
Central	$20,983.5	$26,209.0	$25,260.5	$27,183.1
North Eastman	9,403.8	10,123.8	10,269.0	10,931.0
South Eastman	11,957.8	13,412.3	12,689.2	13,323.3
Interlake	18,376.5	20,366.4	22,931.5	22,728.3
Norman	5,304.1	6,069.3	96,03.0	9,436.5
Parkland	10,495.2	13,216.9	16,000.8	16,638.1
Burntwood	8,160.3	9,989.5	18,038.9	17,644.3
Churchill	225.8	264.9	374.3	416.8
Brandon	12,566.5	12,985.8	11,978.8	11,766.3
Marquette	9,431.2	11,259.5	11,813.8	12,475.4
South Westman	8,879.2	11,141.5	10,292.2	10,437.5
Winnipeg	201,853.5	182,598.4	168,385.4	164,656.7
Manitoba	$317,637.4	$317,637.40	$317,637.4	$317,637.4

[31] The 'actual' column is the 1994/95 dollar total use of services scaled to the 96/97 total budget. All allocations are scaled to that amount. The dollar amounts are in thousands.

NECESSARY FEATURES OF NEEDS-BASED ALLOCATION MODELS

Some Extensions of the Model

If allocations of resources to regions are to be based on the regression model of the sort we have outlined above, then that model should have certain features. It is not enough that we have confidence that the model captures a large component of need. A fundamental requirement of any policy model in this area is relative stability because shifting large components of resources back and forth among regions on an annual basis is not realistic. The model must be practical. However, any reallocative model based on statistical data is bound to be subject to potential fluctuations.

The stability problem is of concern because we know that any statistical model is, by its very nature, imperfect. In our model, we know that some aspects of need are undoubtedly not captured. And, more importantly, some of the data upon which the analysis is based is not completely representative. Despite their established correlation with poor health status, premature mortality rates are also subject to fluctuations due to a number factors which are essentially random. When the units of analysis are relatively small, these fluctuations can be quite significant especially if premature mortality rates are relatively low. Census data are, themselves, subject both to sampling error (possibly undercounting in some areas and overcounting in others) and to random fluctuation. But many of the census variables are believed to be relatively more stable over time. Almost all statistical models are built on data that are imperfect representations of the underlying factors they are designed to represent. They can yield different prescriptions in response to new samples of the data which themselves may include fluctuations such as those we have sketched above.

The method we have developed for building on existing patterns of health care utilization while adjusting for age, gender, socio-economic status and premature mortality is consistent with the major thrusts in the population health literature. As such, this approach has a number of strengths, but is not without its own weaknesses. The analysis is founded on data subject to limitations of the sort described above, and is, therefore, subject to a number of potential criticisms that should be taken seriously in any application. One major objection raised in an earlier presentation of this model was that the results are based on socio-economic status data from the 1986 Census, and are consequently dated. We take this potential threat to the validity of that model seriously, and add to it the cautions about data fluctuations in other variables used in the analysis. In response, we have attempted to develop a model which will be both more current and more stable. That development is sketched below.

The Arguments for Using Longitudinal Data in an Allocation Model

In many areas of policy analysis both analysts and consumers of analysis strive for the most current data upon which to base their conclusions and judgements. In most cases, newer data is a better predictor of the future than old data. But as anyone who has consumed an aged cheddar can attest, newer is not always better. Recent data may provide better prediction in a model when the effects one is trying to predict are proximate consequences of prevailing conditions. Today's weather is almost surely a better predictor of tomorrow's than is the weather from six months ago. The weather on February 28, 1998 may be a better predictor of the weather on March 1, 1998 than is the ten year average data on March 1st weather. On the other hand, on February 28, data on the weather in March from the past ten years is almost surely a better predictor of all of the weather in March than is the weather on February 28. The reason for this is obvious once one pauses to think about it. The weather is based on a broad base of prevailing conditions in the atmosphere. On average, on any given day, those conditions are similar over the long run. But there are clearly fluctuations that have significant impacts on a day's weather in the short run. Therefore, the current conditions are good predictors of the short run, while average conditions are better predictors of the long run.

While factors such as socio-economic status and premature mortality are not as unstable as the weather and are not cyclic, the data we use to represent them are subject to variation due to sampling, rounding other systematic errors and other random fluctuations. Moreover, the effect of socio-economic status on health status is assumed, throughout the literature, to act over time. Failing to get your high school diploma does not necessarily affect your health status immediately, nor does failing to find a job on a first try, or moving into low valued housing, or opting out of the labour force, or becoming a single parent. Experiencing some (or all) of those conditions over a period of many months or years almost certainly takes a toll on your health. It follows that the socio-economic data that one would wish to use to predict health status and resultant needs-based allocation of health care resources should capture not only the most recent status of the population, but also a modicum of its history.

To introduce another analogy to make the point of the cumulative impact of socio-economic status on health, consider how best to evaluate the effects of an exercise regime on muscle tone. If one wanted to predict the muscle tone of a set of individuals who had agreed to undertake a course of exercises at home for a month, data on how hard they exercised the last day of the month (the most recent data) would be a far worse predictor than data on all the exercise they did before that day. The reason, of course, is that the effects of exercise on muscle tone are cumulative. And so, presumably, are the effects of socio-economic status on health. It follows that one would do better using longitudinal socio-economic data as a basis for calculating allocations than simply the most recent data.

But, to return to our analogy, gathering all the data on exercise may be prohibitively expensive or infeasible. Even a sample of data on how much individuals exercised each Tuesday of the month would likely be a better predictor of their muscle tone than the most recent data. The Tuesday sample will still not be a full picture of total exercise. It will still contain errors as a result of sampling, but it will be a better predictor than the most recent data. Again, longitudinal samples of data on socio-economic status can be argued to outperform the most recent data as a basis for calculating allocations. Repeated measures which are aggregated will almost certainly be more robust and may actually be more accurate than a one time proximate measure.[32]

The SERI is based on six socio-economic variables which clearly change over time. It is derived from a relationship with five health status/resource use/lifestyle variables which also vary over time. The census data from which we derived the SERI is well known to be subject to both sampling and rounding error. Specifically, only one in five households fills out the longer Census form which captures the socio-economic data we use. While in the aggregate that sample is no doubt close to representative, when one is using relatively small areas such as some of our municipalities, there is a potential problem of the representativeness of the sample. Moreover, at the enumeration area level the data are rounded to the nearest 5 to preserve anonymity. In small areas, and for some variables with low incidence (e.g. unemployment between the ages of 45 to 56 years) this leads to a number of "0's" and "5's" which approximate the true rates only crudely. And of course, this rounding effect continues throughout the data, although its effects are not as pronounced in larger units of analysis.[33]

In order to get a potentially more valid and stable allocation model, we decided to redevelop the age/gender/SERI model. In doing this, we use not only the most recently available census (1991) data, but we combine it with the data from 1986 used to derive the original model. We believe that a longitudinal model is more likely to reflect true allocations, and is also likely to be more stable - another desirable feature for an allocation model.

[32] This may be so notwithstanding the fact that population mobility may mean that a number of different people are inhabitants of any given area of the two time periods. Of course, if mobility is very high, the usefulness of repeated measures is much diminished. We are currently analyzing the stability of populations over time in the various areas.

[33] By contrast, our measure of premature mortality is based on five years of data and is therefore not likely to be subject to undue random fluctuations.

Developing a Longitudinal Model of Socio-economic Risk for Allocations

The recent availability of 1991 Census data has made it possible for us to broaden the base of our analysis and to build a more potentially valid and stable model of allocations. Again, for purposes of illustration, we concentrate on allocations of ambulatory visits.

Before presenting the results we obtained, it might be useful to document the degree of variability in the 1986 to 1991 census in the variables used in the Socio-economic Risk Index (SERI) and in the five utilization/health status variables used to derive the SERI.[34] In line with our arguments above, those fluctuations furnish a rationale for using a multi-year index as a basis for calculating allocations.

Table 9 shows the correlation at the municipality level among the longitudinal measures of each of the variables. That table also shows the number of municipalities having missing data or zero level values in each year. While many of the correlation are relatively high, some variables show a lower degree of relationship over time. For example, dwelling values correlate at .794 while the correlation coefficient of the two measures of aged 45 to 54 unemployment is only .276. With reported zero values in the unemployment rates in that stratum of 126 (of 271) and 155 (of 277) municipalities in 1986 and 1991 respectively, rounding and sampling errors seem to have played a large role in diminishing the relationship in the latter variable. Even the differences in variables such as percent of the 25 to 34 year old population having completed high school or better, that might be expected to be extremely stable, show considerable variance: a correlation of .497. Since the fluctuations in the measurement of these variables are likely to be independent, the random factors are more likely to cancel one another out. Hence, using an index which combines six such variables is likely to smooth out these random disturbances. An index based on six variables is more likely to be stable and representative of need over time than any single variable. And, of course, to the extent that need is based on a variety of antecedent socio-economic conditions,

[34] The five indicators were standardized fertility rates and acute hospitalizations for four conditions in selected strata: respiratory infections 0-14 years of age and 65+ years of age, male injury and female injury. The years 1991/92 and 1992/93 were used as proximate measures of health status and fertility.

several variables might be expected to provide a more valid representation. By contrast, the five variables representing health status/usage and fertility derived from the Manitoba Health database show much more stability, not being subject to the same sorts of sampling and rounding errors.

Table 9: Number of Municipalities Having Missing Data and Correlations between 1986 and 1991 SERI Variables

SERI Coefficient Variable	# of MUNCODES with:				Correlation	
	Missing		Zero			
	1986	1991	1986	1991	Pears.	Spear.
Unemployment Aged 15-24	6	6	45	105	0.581	0.465
Unemployment Aged 45-54	7	12	126	155	0.276	0.463
Women in the Work Force	5	0	0	0	0.769	0.755
Female Parent Households	9	1	174	83	0.292	0.357
H.S. Diploma Aged 25-34	6	0	3	6	0.497	0.484
Average Dwelling Value	48	55	0	0	0.794	0.819
Fertility Rate	0	0	0	0	0.761	0.622
Hospitalization Rates for:						
Male Injuries	0	0	7	9	0.549	0.361
Female Injuries	0	0	16	16	0.560	0.420
Respiratory Disease						
Aged 0-4	0	0	43	36	0.745	0.557
Aged 65+	0	0	44	36	0.518	0.447

NOTE: There was no imputation for the fertility or hospitalization rates for the Women in the Labour Force, Female Parent Households, and High School Diploma Aged 25-34.

NOTE: Unemployment values were imputed for the Muncodes with an Unemployment Rate = 0.

To take factors such as these into account, we redeveloped the SERI using Census data from both the 1986 and 1991 surveys. Again starting at the municipal level, missing data was imputed to be the regional average data. New data from the 1992/93 fiscal year on five variables describing health care resource use and health status was also available, so the average values of these and the 1991/92 variables were used as a dependent variable against which to establish relationship with the socio-economic variables. The model to derive the new SERI used 12 independent variables: the six SERI variables from each of the two years. The resulting model was highly significant, ($F = 47.55$, $p<.001$) and explained 71.3% of the variance in the aggregated measures of health status and fertility based on 243 municipalities. The coefficients of the independent variables were used to develop the longitudinal SERI: SERI8691. Table 10 shows the parameters of the model using the two years of data.[35]

Table 10: Combined Socio-economic Risk Index Parameters: SERI86/91

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	Prob > |T|
91 Unemployment 15-24	1	0.0703	0.0579	1.215	0.2255
91 Unemployment 45-54	1	0.3382	0.0539	6.272	0.0001
91 Single Female Parent	1	-0.1362	0.0431	-3.161	0.0018
91 High School 25-34	1	-0.0019	0.0516	-0.037	0.9708
91 Female Work Force	1	-0.0616	0.0476	-1.294	0.1970
91 Dwelling Value	1	-0.2821	0.0658	-4.286	0.0001
86 Unemployment 15-24	1	0.1272	0.0594	2.142	0.0332
86 Unemployment 45-54	1	0.1025	0.0565	1.813	0.0711
86 Single Female Parent	1	0.1972	0.0565	3.489	0.0006
86 High School 25-34	1	0.0602	0.0469	1.283	0.2009
86 Female Work Force	1	-0.1850	0.0503	-3.679	0.0003
86 Dwelling Value	1	-0.0902	0.0687	-1.314	0.1903
Constant/Intercept	1	-0.2703	0.0671	-4.030	0.0001

[35] While the 1986 and 1991 variables are often correlated quite highly, (See Table 9) there is sufficient variability over the two measurements to avoid a multicollinearity problem.

The analysis reported in the previous section was repeated with the longitudinal socio-economic variable SERI86/91 replacing the 1986 SERI. Using the same ambulatory visit data the following regression model was fitted:

Visits per capita = F(age1--age21), gender, SERI8691,
(age1--age21)*gender, (age1--age21)*SERI8691,
gender*SERI8691, (age1--age21)*gender*SERI8691)

Again, the regression was highly significant ($F = 47.26$, $p<.0001$). The new index explained a comparable amount of the variance in visits 62.9%. When physician area expected visit rates were calculated from the model, they correlated with mortality to a similar extent as did those derived from the 1986 SERI: Pearson's $r = .470$, $p <.0002$ (vs $r = .500$ for the 1986 index). The slope of expected visits to mortality was .577 ($p<.001$).

The allocations calculated with the 1986 SERI and 1986/91 SERI are highly correlated with a Pearson's r of .975, $p<.0001$. Nevertheless, for policy purposes, the stability of the overall relationship is not the only consideration. Each of the physician areas is a unique entity and large unexplainable fluctuations in allocations in several of them over time would be a matter of concern. We examined the discrepancy between the new and old allocations. Overall, the percentage discrepancy between new and old allocations is +-5.61% with standard error of .59%.[36] Table 11 presents the allocations of per capita visits as calculated using the two indices.

[36] Although about one half of the areas' new entitlements were outside of the 95% confidence interval around the old entitlements, this result is likely attributable to the fact that we are dealing with large samples and so even small differences can fall outside the confidence intervals.

Table 11: Allocations Using Old (86) and New (86/91) SERI with the AGE/GENDER/SERI Model

Physician Service Area	86 predicted visits/resident	86/91 predicted visits/resident
Altona	4.642	5.306
Carman	4.846	5.059
Seven Regions	5.443	6.661
Lorne	4.502	5.185
Morris/Montcalm	4.430	4.701
Morden/Winkler	4.585	5.031
Portage	5.018	5.316
C Wpg adjacent	4.077	3.584
Springfield	3.983	4.119
East Lake Winnipeg	7.204	7.975
Tache	3.881	4.237
Piney District	6.631	7.207
De Salaberry	4.106	4.364
Steinbach	4.470	4.573
E Wpg adjacent	3.974	3.926
East Interlake	7.420	7.323
Gimli	6.233	6.692
Grahamdale	7.249	7.446
Coldwell	8.059	7.886
Rockwood	4.402	4.206
Selkirk	4.793	4.671
Wpg Inner Core	10.190	9.315
Wpg Outer Core	6.712	6.715
Wpg Old St. Boniface	6.586	6.301
Wpg South Central	3.762	3.708
Wpg West	4.143	3.927
Wpg North West	3.806	3.544
Wpg North East	3.927	4.036
Wpg South East	3.062	3.100
Wpg South West	2.648	2.549
The Pas	7.077	7.045
Flin Flon	6.767	6.485
Gilbert Plains	6.086	6.767
Roblin	6.730	6.808
Alonsa	6.122	6.258
Dauphin	5.964	6.322
Pine Creek	10.145	9.672

Physician Service Area	86 predicted visits/resident	86/91 predicted visits/resident
Swan River	5.818	6.141
Thompson	6.316	6.134
Gillam	5.676	6.143
Churchill	5.881	6.551
Leaf Rapids	5.790	6.203
Lynn Lake	5.524	5.596
Norway/Cross	9.930	9.783
Oxford House	10.678	10.449
Island Lake	9.362	8.886
Killarney	4.678	4.569
Melita/Deloraine	4.844	4.971
Souris	4.556	4.843
Virden	5.751	5.962
Russell	5.056	5.588
Minnedosa	5.335	5.700
Boissevain	5.316	5.069
Sioux Valley	8.216	7.109
Brandon	4.561	4.480
North Cypress	5.216	5.213
Neepawa	5.280	5.861
Victoria/S. Norfolk	4.561	4.573

Figure 3 and Figure 4 present comparisons of the 1986 and 1986/91 allocations of ambulatory visits and allows us to see how much variation occurs. Figure 3 plots the 1986/91 Index based allocation against the 1986 based allocation. The tight relationship between the two measures is apparent. Figure 4 shows the actual differences between the two allocations on an area by area basis.[37] The + signs represent confidence intervals.

And again, we can aggregate the results up to the Regional Authority level. The Regional Authority allocations of per capita visits again show a relatively close match (See Table 12). Only 4 of the 12 regions differ by more than 5% in their allocations with only Churchill exceeding 10%. And one can also use this methodology to extend the analysis to all physician services. If one assumes that all physician services should be allocated in a way that corresponds to need for ambulatory care, then the total budget for physician services can be distributed across the regions. Those results are presented in Table 13.

Table 12: Predicted Visit Allocations using 86 and 86/91 Indices

Regional Authorities	86 Index visits/res	86/91 Index visits/res
Central	4.715	5.074
South Eastman	4.892	5.207
Eastman	4.458	4.680
Interlake	5.576	5.526
Norman	6.966	6.845
Parkland	6.374	6.628
Burntwood	7.242	7.083
Churchill	5.881	6.551
Brandon	4.561	4.480
Marquette	5.464	5.770
South Westman	4.965	5.035
Winnipeg	4.565	4.464
Manitoba	4.917	4.917

[37] Areas are presented in order of increasing premature mortality.

Table 13: Allocation of 96/97 Dollars ($1000s) for All Medical Services Unadjusted for Fee Differential

	Actual	1986 Index allocation	1986/91 Index allocation
Central	$20,983.5	$25,260.5	$27,183.1
North Eastman	9,403.8	10,269.0	10,931.0
South Eastman	11,957.8	12,689.2	13,323.3
Interlake	18,376.5	22,931.5	22,728.3
Norman	5,304.1	96,03.0	9,436.5
Parkland	10,495.2	16,000.8	16,638.1
Burntwood	8,160.3	18,038.9	17,644.3
Churchill	225.8	374.3	416.8
Brandon	12,566.5	11,978.8	11,766.3
Marquette	9,431.2	11,813.8	12,475.4
South Westman	8,879.2	10,292.2	10,437.5
Winnipeg	201,853.5	168,385.4	164,656.7
Manitoba	$317,637.4	$317,637.4	$317,637.4

CONCLUSIONS

The regression technique articulated above is a community based and data intensive analysis which uses a two-stage process for reallocating resources for a single sector among geographic regions. We have been using ambulatory visits to physicians as a case study in how to develop a methodology for allocating resources. The analysis has been performed at the physician area level and has used a combination of data from Manitoba Health and the Census. The primary factors we have used in constructing a reallocation model are the age/gender distribution of the population, their socio-economic status as represented by the SERI and premature mortality rates.

The elaboration of the methodology has brought to light a number of methodological and substantive problems. These include the sometimes questionable neutrality of age/gender and other adjustments to establish baseline utilization patterns; the potential importance of interaction effects in needs adjustment formulas; the use of existing patterns of utilization for the derivation of coefficients adjustment; the issue of which contexts are more appropriate for population weighted analyses or unweighted analyses; and the potential usefulness of longitudinal measures of socio-economic factors as adjustments for need.

The neutrality of age/gender adjustments

Our starting point was an attempt to construct an age/gender adjustment as basis for a first stage reallocation of resources. We discovered a somewhat unsettling result. This adjustment captures the current utilization patterns of ambulatory visits across geographical areas correcting for variations in the age/gender distribution. In Manitoba, this pattern leads to allocations of ambulatory physician visits which are regressive relative to premature mortality - a result which parallels effects reported in Eyles et al. 1994. We attribute this regressivity to the variation in utilization patterns across the age/gender strata as a function of socio-economic factors (or other determinants of health). To the extent this may be true of patterns of use in other health service areas, and/or other jurisdictions, we offer a caution regarding the neutrality of a traditional age/gender adjustment as a basis for regional allocation methodologies. Using only an age/gender adjustment as a basis for reallocation risks transferring resources away from needy populations. Using it as a first stage adjuster in a formula which later adjusts for need risks exaggerating the extent of the reallocations from existing patterns required to adjust for need.

Interaction effects and positive relationship with need

As a result of these observations, we chose to build a measure of need into the regression model defining existing patterns of utilization and to do so in a way that took into account interaction effects across the variables in the model. These effects were found to be substantively important in explaining prevailing patterns of utilization.

In the case of ambulatory physician visits, an appropriately positive relationship was found between the average visit rate, adjusted for age, gender and SERI (including all interactions). Consequently, we felt justified in proposing this initial allocation as a baseline for subsequent reallocations. However, if services in other areas, (or in other jurisdictions) are not somewhat responsive to these measures of need, a similar regression technique will not likely lead to a positive relationship between utilization and need. The regression, after all, simply mirrors the prevailing pattern.

While ambulatory physician visits (adjusted for age/gender and SERI) are positively correlated with increasing premature mortality, absolute levels of expenditures on physician services (i.e. taking into account the differential costs of different levels and mixtures of specialists) do not appear to exhibit the same relationship. Thus, deriving a coefficient for adjusting for premature mortality from the existing pattern of service when dollars spent (rather than visits) are the basis of the analysis is not straightforward. By extension, it may not be possible to employ this technique in some other areas and jurisdictions, or it may be necessary to modify it.

On the other hand, Black et al. (forthcoming) has applied the regression technique described here to calculate allocations of short stay hospital allocations. Her analyses show an even stronger fit between allocations calculated in this way and premature mortality. The distribution of hospital resources in the Province may more closely mirror need than the distribution of ambulatory care visits. One might, therefore, consider the use of the parameters and coefficients derived from that set of data to reallocate dollars for physician services and other health care services.

A coefficient for a 2nd stage needs adjustment

The regression technique developed here has allowed us to compare the allocation based on an age/gender/SERI adjustment with the premature mortality of populations in physician delivery areas. While the relationship was found to be in the right direction, i.e. increasing visits were associated with increasing premature mortality, only 25% of the variance in the latter was accounted for by the former. To create a stronger relationship between utilization and premature mortality the relationship between the first stage allocation and premature mortality furnished a basis for a further reallocation. The regression coefficient was used for adding a 2nd stage allocation adjustment in proportion to differences in premature mortality from the provincial mean. Although this coefficient is derived from the data, it too is sensitive to the responsiveness of the existing pattern of services to need and cannot be claimed to have any absolute validity. Again, in other sectors or jurisdictions, the coefficient may take on quite different values, but it is, in principle, calculable and potentially useful as a candidate for use in a reallocation formula.

Another caveat is in order regarding the extension of this methodology to other sectors of health care use. Both ambulatory visits and hospital usage can use age/gender specific utilization data to compute appropriate reallocation parameters. That may be difficult or not possible in other areas of expenditure. There are particular difficulties in using this methodology in the analysis of need for personal care home services. The relationships we have sketched utilize the full age spectrum. It may not be a straightforward matter to apply the technique to a restricted subset of the age spectrum where the need for personal care home beds is at issue. As we have noted, premature mortality is greater among people of lower socio-economic status. Hence, the health characteristics of the population at the highest end of the age spectrum may not show the same gradient in relation to socio-economic status as the population of the whole. So factors identifying need for personal care home beds may be different than those for other health care needs. Indeed, there are no established arguments that the effects of such variables are consistent across the age spectra.[38] This is an issue which warrants fuller study.

Weighting by population

An interesting methodological problem, one potentially tied to some deep theoretically issues, emerges in this analysis. The age/gender/SERI model we have developed is posited on a fundamental assumption. The regional provision of health care services assumes that there are regional differences in need. We believe that it is implicitly assumed in any such model that the areas under consideration are distinct communities which have different needs and that the associated patterns of provision depend on unique characteristics of those areas. If that is the case, we believe that each distinct community should contribute to the calculation of the parameters of need on an equal basis. A small area should be treated the same as a large area in estimating the formula for allocation of ambulatory visits. This approach assumes that the distinctiveness of the characteristics of the people of any area determine the pattern of need, not the number of individuals in that area. Since we are dealing with the entire population of the Province and not a sample, there is no under or over representation of any particular group in the data. In the absence of misrepresentation of the data, population weighted analysis can, at best, result in an analysis favoring provision patterns which resemble those in areas of greater population.

In particular, the population of Winnipeg constitutes roughly one-half of the Province's population. Performing a regression on a population weighted basis would give enormous weight to Winnipeg as the determinant of the "average" provision pattern. The fact that Winnipeg has a large urban population would bias the allocations in favour of the pattern of services in Winnipeg.

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[38] Indeed, a number of our interaction terms of age/gender/and SERI indicate that the effect varies across the spectra.

Put another way, using a population weighted analysis would shrink the smaller areas' contributions to the definition of allocations, relative to those of the larger areas. The resulting average would mask their specific differences and distort their relative allocation of visits. Indeed, if the disparity in size were very great, unique characteristics of small areas would be almost completely swamped by the provision patterns in larger areas. In our case, the municipalities in Winnipeg, which are known to have a rich physician supply and high usage, are much more populous than the other areas. If the analysis were done on a population weighted basis then the average levels of ambulatory visits would largely reflect the patterns in Winnipeg. That pattern would dominate the analysis simply because Winnipeg has more people. Our position is that agricultural areas of small population, or northern remote areas, may well have distinctive characteristics of a socio-economic nature and may vary in their physician supply and access. They constitute potentially different types of communities, and these differences should not be lost in the analysis simply because they are of relatively small size as compared with Winnipeg. Thus, we argue that a population weighted average is not appropriate for our analysis.

But there is a cost to weighting geographic areas equally in the analysis. Given the distribution of population and need in Manitoba, the model becomes quite sensitive to the needs of the worst off. Many of the populations with the worst health and highest premature mortality are located in remote areas and rely on nursing stations for many of their primary care visits. Those areas (about 10% of the cases) have a substantial impact on the results of our analyses. When they are removed from the analysis, and we calculate average utilization patterns as a function of age/gender and SERI, we find that the socio-economic variable plays a diminished role in explaining average usage patterns, and there is a dilution of the relationship between calculated allocations and premature mortality. Thus, it is not possible to use the same coefficient used for the model of the province as a whole when the analysis is based only on the better off regions.

There may be a variety of situations in which it is not clear whether a population weighted analysis is more or less appropriate than a community based analysis. In such situations, the appropriate methodology to use may well be controversial and open to debate. One possible argument against the use of a community based unweighted analysis is implicit in our remark above that the ten percent poorer northern areas, with an even smaller proportion of the population, play a substantial role in determining the coefficients for reallocation.

Longitudinal measures of socio-economic status

Above we have noted the need for stability in any reallocative model. A model which is multivariate and includes a number of independent predictors, promises a modicum of robustness in its predictions. A model which builds in all four primary indicators of need featured in the literature (age, gender, premature mortality and socio-economic status) can be expected to be more stable than one which is more narrowly based. The stability can be further enhanced by using updated data, as it becomes available, to calculate rolling averages, in which the effects of changing conditions are damped by the fact that previous conditions are also represented in the calculations. This has the benefit not only of inducing stability, but is justified theoretically as indicated in our discussion above of cumulative effects and statistical fluctuations.[39]

Caveat

This paper presents a preliminary exposition of a novel and relatively complex methodology for allocating health care resources in accordance with need. From the extended conclusions it is clear that there is much room for discussion and that there is a great deal that could be done to clarify and refine this approach. Hopefully, any such discussions will cast further light on an appropriate way of matching health care resources to need. But one should not lose sight of the well accepted principle that addressing the underlying causes of poor health may be an even more effective way of improving health than shifting health care resources within that sector.

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[39] Clearly all randomness cannot be eliminated. Were analyses such as these ever to be used explicitly a further buffer against randomness, may be prudent. For example, a margin of error in any allocation formula might be built in, explicitly. Areas experiencing a funding level within 5% or perhaps even 10% of their calculated entitlements might be allowed to simply keep their current funding levels (within whatever average increase or decrease might be mandated in any given year). Only areas demonstrating a variation of more than this buffer range might be considered candidates for reallocation.

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APPENDIX A: FIGURES

Figure 1. Allocation of Per Capita Physician Visits vs. Premature Mortality, Stage 1

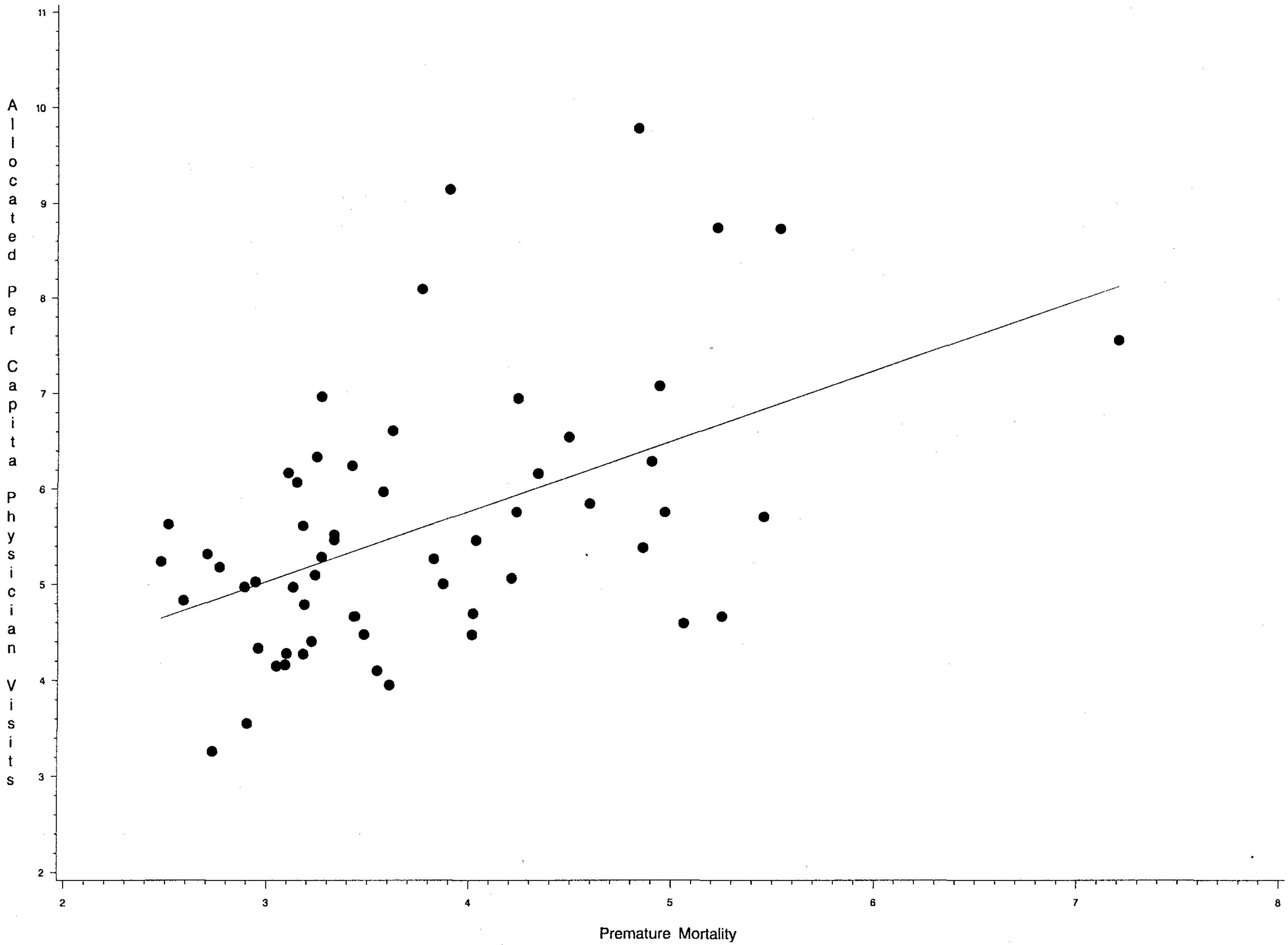


Figure 2. Allocation of Per Capita Physician Visits vs. Premature Mortality, Stage 2

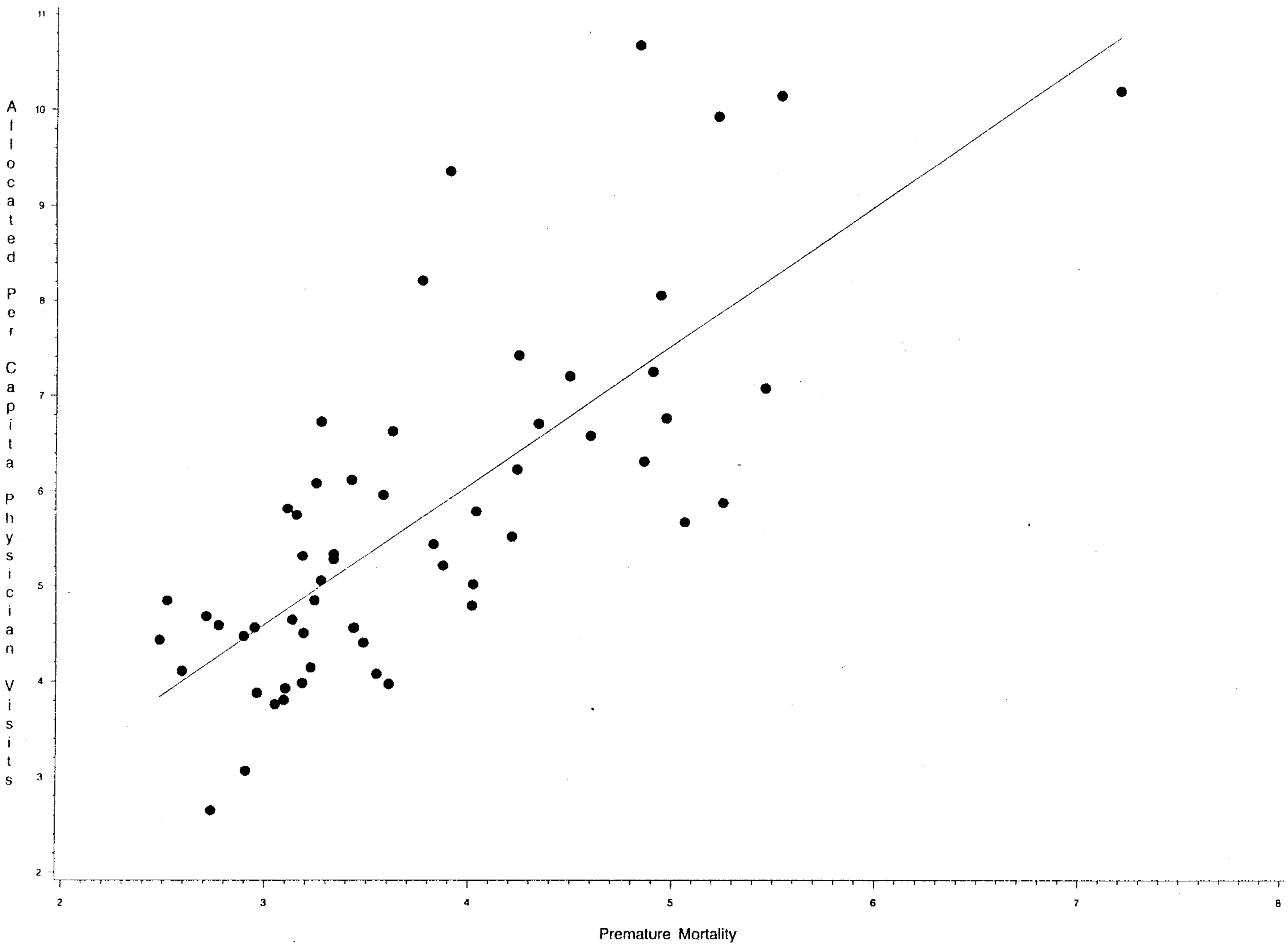


Figure 3. Per Capita Physician Visit Allocations.

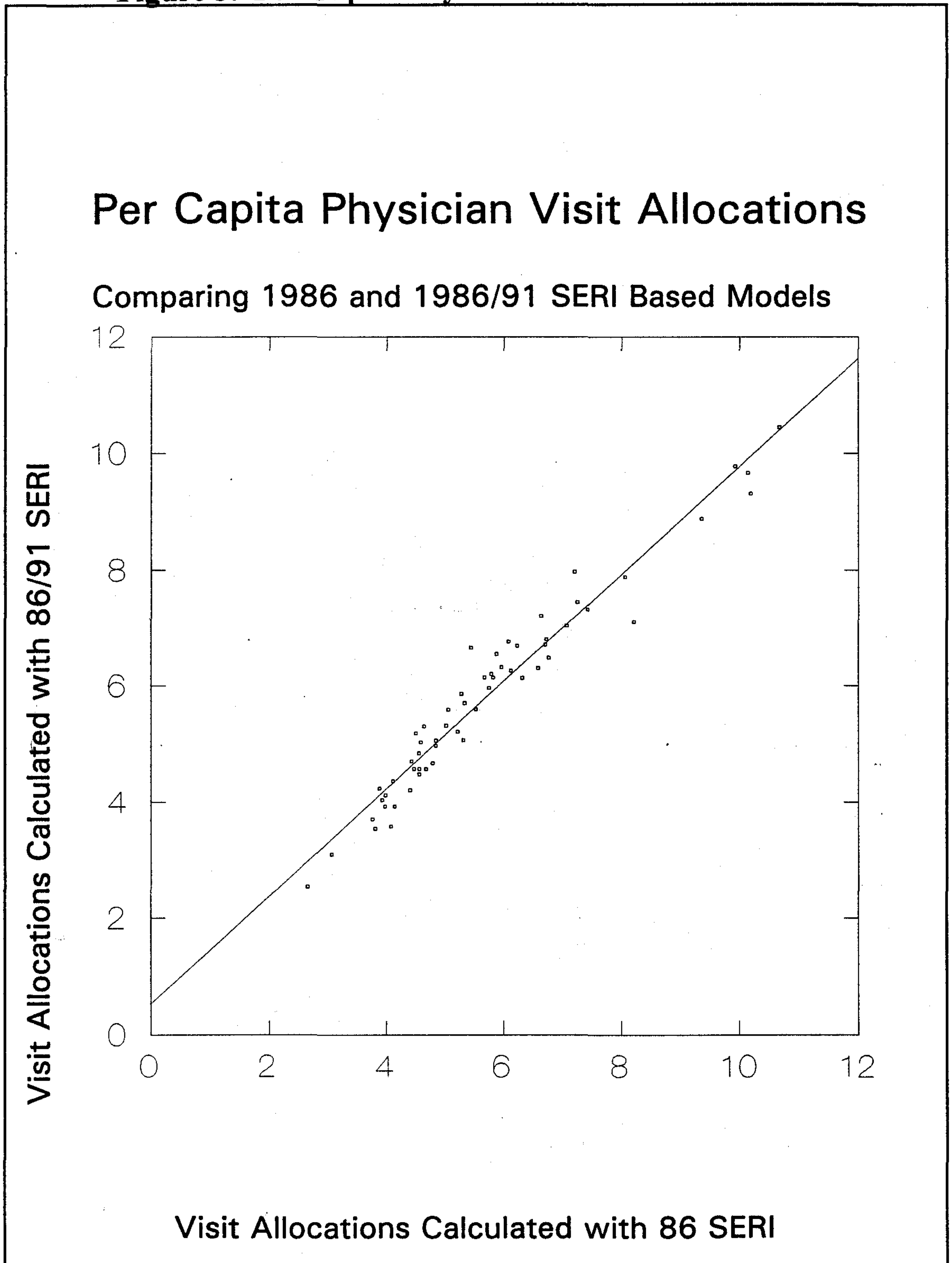
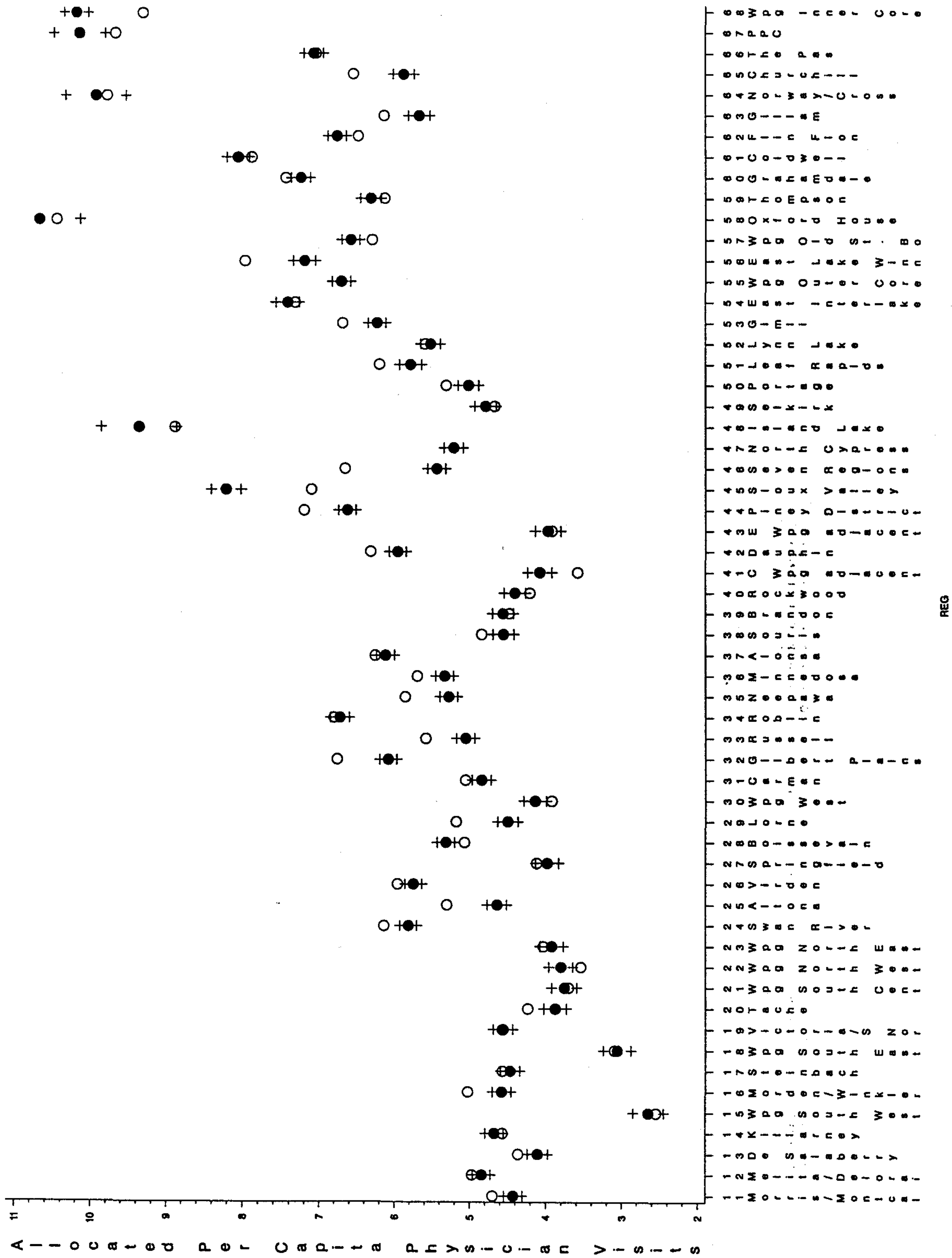


Figure 4. Per Capita Physician Visit Allocations by Physician Areas: Comparing 1986 and 1986/1991 SERI Based Models



APPENDIX B: THE SOCIO-ECONOMIC RISK INDEX

A socio-economic adjustor

The most direct method of taking factors affecting need into account would be to construct allocations of health care resources (such as ambulatory visits) based on data on an individual's characteristics, although community level effects might also enter. Such variables as socio-economic status, health status, health care utilization, as well as a profile of the social, economic and physical environment in which the individual lives and works are all candidates for use as adjustment factors. While the Manitoba Health data capture measures of individual utilization of resources and, indirectly, measures of health status, we do not have access to measures of individual socio-economic status. We are, however, able to supplement individual-level health information with measures from the Census of socio-economic characteristics of the area of residence.

In the earlier works cited (Frohlich and Mustard, 1994) one of our operating assumptions was that there is a linear relationship between individuals' health and socio-economic variables. Preliminary exploration of the data appeared to support that assumption. In that work we employed a multiple linear regression model to build the SERI index to serve as an indicator of relative need.[40] The dependent variable for purposes of identifying socio-economic factors associated with poor health was an index referred to as a Baseline Test Index (BTI) constructed from five indicators: standardized fertility rates and acute hospitalizations for four conditions in selected age or gender strata: respiratory infections 0 - 14 years of age and 65+ years of age, male injury, and female injury.

[40] It should be noted that the reporting of census data when events in a unit of analysis are fewer than 5 utilizes a random rounding algorithm which records the value of the particular variable as zero or 5. Taking these at face value creates some variables of questionable validity.

Using data from 282 Municipalities and a broad swath of socio-economic variables from the 1986 Census, six variables were found to be closely related to the BTI and were combined into an index: the Socio-economic Risk Index (SERI) . Three of these were positively related to poor health:

- the percentage of the labour force unemployed: ages 15 to 24,
- the percentage unemployed between 45 and 54, and
- the percentage of single parent female households.

Three were negatively related:

- the percentage of the population between the ages of 25 and 34 having graduated high school,
- the percentage of females participating in the labour force and
- the average dwelling value.

The resulting Index, SERI, was shown to be strongly related to a number of measures of health status and resource utilization.