LONGITUDINAL WEIGHTING AND ANALYSIS ISSUES FOR NATIONALLY REPRESENTATIVE DATA SETS

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INTRODUCTION

We review and examine utilization of weights as part of an analysis strategy where 1) longitudinal information is available for sample of individuals, e.g., measurement at two or more points in time for the same individuals (Duncan and Kalton, 1987), and 2) where weighting and imputation schemes have clear trade offs with respect to precision within domains (Lepkowski, 1989). While the issues of if and how to employ weights remains a subject of spirited debate at both the theoretical and technical levels (Kalton, 1989; Hoem, 1989) we approach the longitudinal weighting problem with the aim of empirically evaluating the influence of various types of weights, e.g., longitudinal, cross-sectional, and weighting adjustment factors such as nonresponse, on one's ability to make appropriate inference from large, relatively complex nationally representative longitudinal data files which, because of the resources involved, are usually sponsored and conducted by the federal government, e.g., Survey of Income and Program Participation, National Medical Expenditure Survey, or National Long Term Care Surveys. Our approach requires the following elements: 1) measurement of at least two time points for a sample of individuals, 2) associated measurement of gross change over time for said individuals, 3) various sample weights, and 4) complete sample design information including nonresponse adjustment strategies employed in the study.

These four groupings of information which are necessary for our evaluation are available from federally sponsored studies but are not normally available from one source or included on public use data files. Rather, the analysis which we conduct must be based on information about a particular study design that is generally used uncritically, e.g., information on variable calculation and weighting including the ignorable nonresponse assumption. For example, information necessary to calculate the Taylor Series variance approximation is not a normal part of federal tape release standards just as the various adjustment factors beyond the base weight are not normally separately identified on a public use data file. Thus, availability of the requisite information on a study drove our choice of a nationally representative dataset to examine. Another could just as easily have been chosen.

The National Long Term Care Surveys, surveys of the aged population were conducted in 1982, 1984, and 1989 from a list of aged Medicare beneficiaries. Briefly, cross-sectional and longitudinal population estimates are available from the study with excellent coverage of the target population from a continuously updated Medicare program enrollment file which includes detailed information on use of covered medical services by individuals over time. Detailed information is available on weighting and information is available on weighting and imputation strategies as well as study design data whose characteristics allow measurement of gross change as well as period estimation. The survey itself measures functional disability with extensive questionnaire batteries on activities of daily living, instrumental activities of daily living, range of motion, medical conditions, and social integration. Social, economic, and demographic data are also collected at each time point.

Thus, the minimum criteria for examining the inference of sample weights on the measurement of gross change of individuals over time is present with the NLTCS. We consider the case of change between 1982 and 1984 for individuals who received a detailed interview in both years. We first employ a grade of membership technique to assign a 'level' of membership to each individual in the study at the two time points (Manton, Tolley and Woodbury, 1989). These grades of membership or g_{ik}s have properties such that we may regress then on the weights to determine to what extent these measures, which are calculated completed independently of the weights, predict their values. F-test and R^2 values will be examined. Several weights are considered: both longitudinal and cross-sectional.

Those empirical tests employing notions of grade of membership in the longitudinal setting may be applied to any study where the necessary design information is available. This particular application has the advantage of a relatively simple design and remarkably good coverage of the target population.

BACKGROUND

Substantial interest in panel surveys, of late, has been addressed by numerous articles, research reports, and research conferences; while the contents of the latter were eventually published in a the book *Panel Surveys* (Duncan and Kalton, 1987; Hoem, 1985; Kasprzyk et al., 1989). Classification, design, and analysis of panel survey data have all been examined in some detail in the above and other publications. We would adopt Duncan and Kalton's definition of a panel survey as 'one in which similar measurements are made on the same sample at different points in time.' They note that panel surveys are often called longitudinal surveys. Study objectives and the practical realities of resource availability. Given that measurement of gross and net change is a preeminent consideration, then a panel or longitudinal survey offers great analytic potential. The reader should note that Heckman and Robb (1989) take issue with this view, arguing that appropriate analysis of repeated cross-sectional surveys offers surprising analytic potential for measurement of change over time, e.g., program effects

However, substantial survey methods issues remain to be resolved with any panel study design and application. It further seems reasonable to discuss them prior to development of weighting and analytic issue discussion. Specific discussion of efficiency in the frame or estimation of the target population, estimation of rare population characteristics, sample supplementation, and loss to follow-up as part of nonresponse, mode of administration, and response effects is necessary in the special context. of longitudinal surveys.

As different study designs deal with these issues in different ways and as others have classified and defined nonsampling error (Kish, 1965; Groves, 1990), we examine these particular elements of nonsampling error in terms of the survey used in the analysis. The Long Term Care Survey uses the aged U.S. population as a target population using the Medicare enrollment list as a frame it achieves approximately 97% coverage (alien residents for less than five year, certain civil servants, and persons with fewer than forty quarters of covered employment are not eligible). A screener interview conducted by telephone and in person, if necessary, roughly screens out the nondisabled population. This technique allows the conduct of detailed interviews with the community and institutional disabled (4,128 in 1982 and 1984) to achieve high levels of precision on a cross-sectional basis for a rare population and allows sufficient unweighted numbers for analysis of transitions between and among functional states such as ADL, IADL, and death (Manton, 1988). As the study sample frame is the Medicare enrollment list, each successive sample point, say 1984, may be supplemented by a sample of individuals who turned sixty-five since the previous sample point, 1982. Further, continuous information is available on use of covered services from the Medicare bill paying function. These two administrative features of the Long Term Care Survey design 1) substantially reduce the potential for loss to follow-up, 2) providing for both cross-sectional and longitudinal analyses at each time point after t_1, and 3) reduce variable error due to left censoring, e.g., mortality before screening but after selection. Loss to follow-up has been minimized by use of Medicare administrative devices, e.g., current address, use of services. However, additional devices include use of Census Bureau interviewers, sample supplementation from a reserve sample, and confirmation of mortality status with Medicare. Using this ensemble of techniques each of the three Long Term Care Surveys (1982, 1984, 1989) achieved very high response rate (≥95%) with the greatest loss to follow-up being mortality. Last, selection was an administrative process not concerned with mode of administration while screening for functional limitations was designed to be a robust telephone procedure which required personal administration in 20% of cases. A temporally distant detailed personal interview follows; to be repeated at irregular intervals until death. This design arguably offers little opportunity for treatment or response effects, whatever their duration.

The Long Term Care Surveys both meet the criteria for a panel study while presenting design characteristics that adequately address methodological issues associated with collecting longitudinal data while preserving the ability to estimate cross-sectional means and variances. In addition, the use of uniform questionnaire batteries and interviewer procedure with a trained staff reduces the potential for measurement error in the measurement of gross change where nonresponse and conditioning are clearly controlled via design.

The use of model based versus finite population approaches to analyses of data, e.g, the weighting issue may be examined with this particular data set under the assumption that substantial levels of bias and variable error in the study have been controlled via design. Further, one should note that a weighting strategy was used to adjust for nonresponse and item/person imputation was not performed. Our narrow purpose is to examine the predictive ability of an unweighted set of coefficients (g_{ik}s) from the grade of membership technique where the weights and components of the weights available for use with the NLTCS data file are the dependent variable and where the coefficients are not connected in <u>any</u> prior way to the weights themselves, e.g., they are calculated with unweighted data.

The next sections present detailed information on the data and methods which enable the analysis

DATA

Development of the Survey

The 1982 and 1984 NLTCS are detailed household surveys of persons aged 65 and over who manifest some chronic (i.e., defined as lasting or expected to last 90 days or longer) Activity of Daily Living (ADL) or Instrumental Activity of Daily Living (IADL) impairment. The sample for the surveys was drawn using a two-stage procedure. In 1982, 35,789 names were drawn from the Medicare Health Insurance Skeleton Eligibility Write-Off (HISKEW) file. The persons were then screened by either telephone or personal visit to see if they manifested a chronic ADL or IADL impairment. When the screen identified a person living in the community with a chronic impairment, a detailed household interview was conducted which gathered information on medical status (diagnoses), functional status (presence of ADL, IADL or other functional impairments), need for special equipment and/or caregivers to deal with impairments, income and assets, health care service use and sources of payment, use of Medicare or Medicaid benefits, and housing and living arrangements. Of particular note in the survey were detailed questions on the number and type of informal caregivers. Though identified in the sampling process, institutionalized persons were not interviewed in 1982.

In 1984, a different sampling procedure was utilized. First, all persons who reported chronic disability on the 1982 screener or who were not screened due to being institutionalized on April 1, 1982, and who survived to 1984 were interviewed regardless of their 1984 functional status. Second, from the original 25,541 persons who did not report functional impairments in 1982 (and who were not institutionalized), a random sample of 47% (approximately 12,100 persons) was drawn and subjected to the same screening procedure as in 1982. Another difference from 1982 was that 4,916 persons who became 65 between 1982 and 1984 were screened so that, in addition to having a longitudinally followed sample in 1984, the full cross-section of persons aged 65 and over in 1984 could be evaluated. In addition, persons who were in institutions in 1984 were interviewed with a specially designed instrument containing a number of questions on institutional use in the interim period an the sources of payment for those services. The interview instrument used for the community population was nearly identical in 1984 to that used in 1982. A final major difference between the 1982 and 1984 surveys was that a "next of kin" interview was conducted for persons who died between 1982 and 194. This interview collected extensive data on the medical service use and expenditure surrounding death.
detail.

METHODS

Next, we briefly describe the GoM model. Let us assume that we have discrete response data, where each of i persons (i = 1, 2, 3, ..., I) has one of L_j responses for the jth variable and each such response is represented by the binary variable, X_{ijl}. The basic form of the model assumes that the probability $X_{ijl} = 1.0$ can be predicted by K sets of two types of coefficients. The first type of coefficient, g_{ik}, represents the degree of membership of the ith person in the Kth group where the coefficient is estimated under the constraints that $0 \le g_{ik} \le 1.0$ and $\sum_k g_{ik} = 1.0$. The second type of coefficient is written λ_{kjl} which represents the probability that a person exactly like the kth type (i.e., $g_{ik} = 1.0$) has the lth response to the jth variable. With these definitions the basic model can be written as,

$$\text{Prob}(X_{ijl} = 1.0) = \sum_k g_{ik}\, \lambda_{kjl}\,. \tag{1}$$

Estimation of (1) is done by maximum likelihood procedures. One of several forms of likelihood may be used for estimation depending upon the probabilistic structure assumed. One possibility for the simple individual response is a conditional multinomial form or,

$$L = \prod_i \prod_j \prod_l \left(\sum_K g_{ik}\, \lambda_{kjl}\right)^{X_{ijl}}. \tag{2}$$

A second estimation approach, which is asymptotically equivalent, but which has certain desirable numerical properties, is an unconditional Poisson likelihood function, in which the sum of λ_{kjl} over j and l are normalized to equal the number of questions j or,

$$L = \prod_i \prod_j \exp\{-x_{ijt}\, \lambda_{ijt}\} \prod_{l=1}^{L_j} [\lambda_{ijl}]^{x_{ijl}} \tag{3}$$

where $\lambda_{ijt} = \sum_l \lambda_{ijl}$ and $x_{ijt} = \sum_l x_{ijl}$.

In other applications it is possible to extend the structure of the model to an empirical Bayes formulation where λ_{kjl} are assumed to follow a Dirichlet distribution (producing a negative binomial likelihood function), to an aggregate data form where limits are allowed to have multiple responses (leading to a Poisson or negative binomial form for the event frequencies), or to a contaminated data form where dependence is assumed to occur between cases (e.g., for genetic effects in twin pairs or spatial effects on disease event clustering say in villages; see Manton and Woodbury, 1990; and Woodbury and Manton, 1990).

Two general statistical issues are a.) the statistical properties of the parameters g_{ik} and λ_{kjl}, and b.) the properties of the likelihood function values given the boundary constraints on the parameter space.

The first point to recognize about the properties of the parameters is the different nature of the g_{ik}. There is a tendency to interpret the g_{ik} as posterior probabilities of classification in K discrete groups. The g_{ik} are not posterior classification probabilities but mathematical mixing coefficients. This can be most simply identified by examining the likelihood function for the discrete mixture problem where the indices l and j are subsumed in m for convenience, or,

$$L = \prod_i \left[\sum_K P_K \prod_M \Lambda_{MK}{}^{x_{im}} \right] \quad (4)$$

It is apparent that (2) and (4) are mathematically distinct with the discrete mixture probability P_K representing the exact classification of a case into one of K discrete class (e.g., different orders of summation and multiplication over K). In the GoM model this would correspond to the special case that, for all i, the g_{ik} coefficient adopts the value of 1.0 or 0.0. Thus, for a discrete mixture model with truly K classes the addition of more variables would tend to cause the P_K to approach 0 or 1.0 (i.e., the classification into one of the K discrete classes would be better determined). In a model which is truly a fuzzy partition model, with the addition of variables that are sampled from the same measurement domain, the g_{ik}s would tend to the appropriate mixing coefficient values, i.e., not necessarily zero or one.

Given the correct mathematical interpretation of the g_{ik}s we now may ask about its (and the λ_{kjl}) statistical properties. These properties can be developed by generalizing the arguments of Kiefer-Wolfowitz (1956) for models with infinitely many so-called "nuisance" parameters. Specifically, in analogy to Kiefer-Wolfowitz, one has to show that certain properties hold for the fuzzy partition mathematical model. Heckman and Singer (1984a,b) showed how those conditions could be generalized for the discrete mixture case which they then used in a hazard modeling scheme where the discrete mixture was used to represent the effect of unobserved variables on the hazard function.

The most critical property in the demonstration is that of the property of identifiability. This is the major definition that has to be altered from the Kiefer-Wolfowitz formulation since they used the expectation of the nuisance parameters in their likelihood formulation, and thus did not retain the full information on individual responses. This information is not integrated out in either form of the likelihood function. In Tolley and Manton (1990a) it is shown how the observed data may be broken into subsets or packets of data. Heuristically, these packets of information provide a solution for the set of g_{ik} and λ_{kjl}s in a model of order K. The estimation is based upon the stipulated constraints on the g_{ik} and λ_{kjl} estimates and upon implicit constraints between the G and Λ spaces, i.e., given the data and one set of parameters the other set is determined up to a certain number of moments. For fixed K it can be shown that, as the numbers of cases increase, the number of packets increase. As the number of variables, J, increases the amount of information per packet increases. Therefore, constraints on the moments of the distribution of the g_{ik} effectively increase information attributed by increases in J. Thus, even though individual parameters are estimated, the information on the parameter space can increase with either increases in sample size or the number of variables for a given order (i.e., for a fixed K) model. With the increase in information it can be shown, in an involved proof, that the estimates of the λ_{kjl} are asymptotically consistent (Tolley and Manton, 1990a).

The estimates of the individual g_{ik}s are, however, not consistent but the moments of the g_{ik} distribution up to the identifiable limit are consistently estimated. The moments of the g_{ik} distribution that may be identified are those with total degree at most equal to the number of questions, J, that are used in the data gathering. Thus, the g_{ik} distribution can often be identified up to a large number of moments and thus well approximated. The set of all distributions with all moments of order J or less equal may be said to define an equivalence class of distributions. Since distributions with differences of moments of order greater than J cannot be distinguished in the data one can only make inferences within the distributions in the equivalence class.

This is not a restrictive assumption since J is often a large value. Indeed, most commonly used multivariate statistical models impose much more stringent conditions on the number of moments utilized. For example, multivariate normal procedures use only the first and second degree moments. Factor analysis or principal components analysis only utilizes the covariance (or correlation matrix) so that the number of estimable parameters is limited to the number of unique elements in that moments matrix. Even if higher order moments are important in characterizing the distribution of responses such models do not utilize the information.

In the GoM model, because the individual g_{ik}s are estimated, no a priori constraints are imposed on their distribution--only the identifiability criterion for a model of order K (clearly K must be less than J; the exact number of pure types identifiable depends on the structure of the problem but in general, the number of pure types practically estimable is much less than J). Of course, this greater flexibility is purchased at the expense of much higher computational effort since [K-1 x I] g_{ik} parameters must be estimated in a nonlinear maximization routine with appropriate boundary constraints. Nonetheless, with appropriate specialized numerical algorithms and dedicated super-micro computers quite large analyses (e.g., 50,000 episodes with $\sum_j L_j \geq 200$; where K =6 or more) have been conducted. The current rapid increases in computational capacity makes attractive the treatment of inference in an Nth order moments equivalence class as a considerable generalization of standard statistical models by not requiring specific distributional assumptions. Clearly the statistical resolution (i.e., the detail about the phenomena that may be identified) is bounded by the limits of the available sample and measurement spaces but that is no different than standard statistical approaches. The GoM formulation can utilize increases in information to generalize one's model specification with only moderate assumptions.

RESULTS

Two subsections are presented. First, we present a longitudinal grade of membership analysis based on 4,182 observations and completed interviews in both 1982 and 1984. Second, regression of g_{ik}s on the various weights are examined to begin to address the question of the utility of weights on this cohort study's analyses. Several models were examined that contained varying number of pure types. Likelihood chi-square tests with the number of degrees of freedom considered showed that the appropriate number of pure types was seven (K = 7). Table 1 is based on 4,182 = N and are divided into interval variables (those which contribute to the unique solution), external variables crossed with time (1982-1984 combined variables), and other external variables, all of whose values are calculated contingent on the solution based on the internal variables. All variables are present for 1982 and 1984 except for the cross survey variables which combine the information for each year. Several items from each category of variables are important in the following regressions.

In the table, the first column is the variable name along with its categories. For example, in Table 1, the first variable is "needs help with eating." This is a 1982 variable. The response categories for this variable are "yes" and "no." To conserve space and simplify the visual presentation, only the yes response is included in the table. The second column, labeled frequency, is the percent of survey population from that year who answered yes to that question and were subsequently interviewed in 1984. Thus, 3.78% answered yes for eating in 1982 and 5.88% in 1984. The next seven columns represent the seven pure types. The row for the answer "yes" represents the probability that someone who is 100% like a given type will have this response to a question. We observe that a yes answer is a property of pure type seven. Persons who are 100% like this type have a 35.4% probability of responding "yes" to this question, while this probability for the remaining types is zero. This clearly indicates that anyone who answers yes to this question must be, at least in small part, a member of pure type seven and that this observation could not be a 100% member of one of the other types though the observation could have a high grade of membership score for one or more of these other types. The variables in the table all follow this interpretation and format. For those questions that do not have a yes/no response, such as "difficulty climbing stairs," responses (no, some, very, can not) were coded. All of these response categories are included in the table. The interpretation of variables values with more than two responses is similar to that described for dichotomous response variables. For example, the population frequency for the "no" response to "difficulty climbing 1 flight of stairs?" is 18.10% in 1982. For pure type five, the probability is 22.42%. This implies a greater than average difficulty in performing. This activity is a characteristic of pure type five. For the multiple response questions, some responses were missing. Therefore, "missing" was included as a possible response in order to avoid bias in the result. To ease the complexity of the presentation the row is not reproduced in the table.

The characterization of the pure types is aided by the representation of the λ_{ijk}s for each category of each variable, enabling the evaluation of the relative importance of each variable category to each pure type. Detailed examination of the table is summarized in the following discussion where a brief label is applied to each pure type and its main characteristics are highlighted for internal and external cross tabulated variables.

Type One: "The Young and Healthy" have some IADL difficulties but are well educated on the whole.

Type Two : "Broken Bones" describes a group that does not exhibit medical conditions other than hip and other bone fractures.

Type Three: "Cardiopulmonary Problems" is composed entirely of males who have few ADL problems which require help, e.g., bathing is one, and few IADL problems.

Type Four: "The Impaired" have substantial ADL problems, e.g., dressing, bathing and toileting, while representing degenerative disease that is more often chronic than lethal, e.g., arthritis.

Type Five: "The Cognitively Impaired" are quite old and are retarded/senile with some stroke and arteriosclerosis reported.

Type Six: "Moderately Impaired with Some Senility" shows a pattern of substantial IADL problem levels with no ADL limitations.

Type Seven: "Old and Very Frail" represents a heavy loading of care needs across each ADL and IADL item. Substantial inability to perform higher level functioning items (IADL2) are also present.

These seven pure types represent a heterogeneous disabled population in the community over time. The diversity of patterns of illness and adaptation to it, illustrates disease etiology as well as social support arrangements for the aged.

Regressions

The long term care survey consisted of a two-stage sample design. The primary sampling units corresponded to counties on counties or county clusters and were selected with probability proportional to the estimated size of the Medicare population. At the second stage, a sample of Medicare enrollees was selected stratified by age and reason for entitlement. The second stage sampling rate was inversely proportional to the first stage sampling rate, resulting in equal overall probabilities of selection.

In order to produce unbiased estimates of survey population characteristics, a series of weights were computed for each year of the LTC. The initial base weight was refined to be the inverse of the overall selection probability, and therefore constant for all sample members. A series of adjustments was applied to these base weights to account for various types of nonresponse. The final weight constructed for persons completing a detailed interview was equal to the product of the initial base weight, an adjustment factor for non-interview at the screener, an adjustment factor for non-interview at the detailed, and two post-stratification ratio adjustment factors to known population totals. In addition to the cross-sectional weights, a longitudinal weight was constructed for cohort analyses across the two survey years. Persons completing a detailed interview in both years received a longitudinal weight, adjusted for nonresponse via post-stratification.

We were interested in investigating whether the variation in the variation in the final weights resulting from applying different adjustment factors to different classes of sample members could be explained by the individual Grades of Membership for the seven pure types. If this were the case, one could argue that the definition of the pure types in the GoM analysis adequately explained the different patterns of nonresponse occurring in the sample, and that the weights were "noninformative" given the Grades of Membership.

To investigate this, we conducted regression analyses in which the level of the adjusted weights were modeled as a function of the individual Grades of Membership (g_{ik}s, k = 1,..., 7) for each of the seven pure types. Three weights were considered, the cross-sectional weights for years 1982 and 1984 and the longitudinal weights constructed for two-year cohort analyses. The results presented in Table 2, indicate that the g_{ik}s are significantly associated with the adjusted weights in 1982 and longitudinally but not in 1984, thus indicating a correlation in two of these circumstances. However, the R^2 statistics are such that only a small portion of the variation in the adjustment is explained by the g_{ik}s.

SUMMARY/FURTHER RESEARCH

We wish to examine the "informativeness" or correlation and ignorability of weights in a longitudinal survey and by implication, the utility of weights in longitudinal data analysis with a panel study design. In doing so we have employed data from the 1982-1984 Long Term Care Survey panel, grade of membership techniques for longitudinal data analysis, and regression analysis of grade of membership g_{ik}s on the various weights of interest from the NLTCS data file.

Findings include 1) a complex structure of pure types (K = 7) in the longitudinal data, supporting previous findings of substantial heterogeneity on health and other variables in the aged population and 2) regression results which indicate that, in this particular design, the weights are correlated with the g_{ik} values from the grade of membership methodology in two cases but R^2 was very low. The test performed was, in the case of longitudinal weights, a test of adjustment weighting factors as the study was a self-weighting sample after screening; the population of interest for panel study analysis. Concern naturally exists about the generalizability of our results across survey study designs where stratification and clustering play a much larger role than in the study at hand. We plan to conduct several additional analysis to test the hypothesis of no difference for the inclusion of weights in analyses via:

1) Conducting GoM analyses with and without weights
2) Examining weighted and unweighted B's using the surregger special software, and
3) Producing weighted and unweighted λ_{ijk}s for examination.

We believe these analyses will directly address the issue of informativeness of weights as well as the ignorability issue.

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Table 1: Seven Pure Types (K = 7) Grade of Membership Analysis of ADL/IADL, Medical Conditions, Health and Sociodemographic Variables: Medical Condition and Functioning Variables for Perons Interviewed in 1982 and 1984 (N = 4,182)

		Pure Types						
	Frequency	I	II	III	IV	V	VI	VII
Needs Help With:								
Eating	3.78	0.00	0.00	0.00	0.00	0.00	0.00	35.40
	5.88	0.00	0.00	0.00	14.63	0.00	0.00	47.35
Get In/Out Bed	21.59	0.00	81.01	0.00	0.00	0.00	0.00	100.00
	26.35	0.00	63.66	0.00	100.00	0.00	0.00	100.00
Get About Inside	36.18	0.00	100.00	0.00	0.00	0.00	0.00	100.00
	40.05	0.00	100.00	0.00	100.00	0.00	0.00	100.00
Dressing	15.66	0.00	0.00	0.00	0.00	0.00	0.00	100.00
	18.72	0.00	0.00	0.00	83.08	0.00	0.00	100.00
Bathing	37.35	0.00	100.00	100.00	0.00	0.00	0.00	100.00
	43.93	0.00	99.95	0.00	100.00	0.00	0.00	100.00
Toileting	16.38	0.00	42.72	0.00	0.00	0.00	0.00	99.36
	22.14	0.00	34.09	0.00	92.16	0.00	0.00	100.00
Bedfast	0.24	0.00	0.00	0.00	0.00	0.00	0.00	2.03
	0.74	0.00	0.00	0.00	0.00	0.00	0.00	6.31
No Inside Activity	0.53	0.00	0.00	0.00	0.00	0.00	0.00	4.52
	1.48	0.00	0.00	0.00	0.74	0.00	0.00	12.46
Wheelchairfast	2.32	0.00	0.00	0.00	0.00	0.00	0.00	20.86
	3.56	0.00	0.00	0.00	0.00	0.00	0.00	31.42
Needs Help With:								
Heavy Work	72.50	14.12	100.00	100.00	47.76	100.00	100.00	100.00
	72.12	5.79	100.00	100.00	100.00	100.00	100.00	100.00
Light Work	18.13	0.00	0.00	0.00	0.00	40.77	0.00	100.00
	23.77	0.00	0.00	0.00	100.00	0.00	0.00	100.00
Laundry	40.79	0.00	61.41	100.00	0.00	100.00	36.26	100.00
	43.35	0.00	30.01	0.00	100.00	100.00	0.00	100.00
Cooking	26.33	0.00	0.00	0.00	0.00	100.00	0.00	100.00
	31.92	0.00	0.00	0.00	100.00	100.00	0.00	100.00
Grocery Shopping	58.23	0.00	100.00	100.00	0.00	100.00	89.55	100.00
	60.09	0.00	100.00	0.00	100.00	100.00	58.21	100.00
Get About Outside	58.70	0.00	100.00	0.00	0.00	92.13	22.10	100.00
	61.88	0.00	100.00	0.00	100.00	86.93	28.95	100.00
Traveling	55.83	0.00	100.00	0.00	0.00	100.00	78.56	100.00
	60.23	0.00	100.00	0.00	100.00	100.00	60.60	100.00
Managing Money	24.20	0.00	0.00	0.00	0.00	100.00	0.00	100.00
	29.36	0.00	0.00	0.00	100.00	100.00	0.00	100.00
Taking Medicine	18.94	0.00	0.00	0.00	0.00	98.13	0.00	100.00
	23.08	0.00	0.00	0.00	85.49	88.90	0.00	100.00
Telephoning	13.92	0.00	0.00	0.00	0.00	100.00	0.00	71.89
	16.62	0.00	0.00	0.00	18.88	100.00	0.00	91.69
Difficulty Climbing 1 Flight Stairs								
No	18.10	46.81	0.00	0.00	16.23	22.42	0.00	0.00
	17.78	47.65	0.00	0.00	0.00	8.15	0.00	0.00
Some	29.27	53.19	0.00	0.00	83.77	53.97	3.28	0.00
	27.84	52.35	14.68	38.93	0.00	91.85	1.25	0.00
Very	33.14	0.00	64.69	100.00	0.00	23.61	75.18	19.34
	31.90	0.00	63.46	61.07	51.36	0.00	79.48	13.80
Cannot	19.50	0.00	35.31	0.00	0.00	0.00	21.54	80.66
	22.48	0.00	21.86	0.00	48.64	0.00	19.27	86.20
Difficulty Bending for Socks								
No	43.30	89.34	0.00	0.00	86.09	71.97	0.00	0.00
	44.27	93.68	35.77	0.00	0.00	90.43	0.00	0.00
Some	28.33	10.66	57.83	69.46	1.91	28.03	55.36	0.00
	26.58	6.32	43.46	100.00	48.98	9.57	56.04	0.00
Very	19.38	0.00	42.17	30.54	0.00	0.00	44.64	31.46
	17.61	0.00	20.77	0.00	51.02	0.00	43.96	16.08
Cannot	8.99	0.00	0.00	0.00	0.00	0.00	0.00	68.54
	11.54	0.00	0.00	0.00	0.00	0.00	0.00	83.92
Difficulty Holding 10 lbg. Pkg.								
No	30.19	78.62	0.00	0.00	39.53	1.85	0.00	0.00
	28.90	80.61	0.00	0.00	0.00	0.00	0.00	0.00
Some	18.10	21.38	1.69	2.25	47.73	23.48	14.09	0.00
	17.09	19.39	29.38	0.00	0.00	59.03	21.10	0.00
Very	17.65	0.00	31.18	9.75	1.91	38.65	36.67	0.00
	15.17	0.00	31.83	0.00	14.55	1.67	43.99	0.00
Cannot	34.06	0.00	55.14	0.00	0.00	24.02	49.24	100.00
	38.84	0.00	38.88	0.00	85.15	22.30	34.91	100.00
Difficulty Reaching Over Head								
No	54.58	100.00	77.27	0.00	99.61	93.40	0.00	0.00
	56.84	100.00	100.00	0.00	0.00	100.00	0.00	0.00
Some	21.86	0.00	22.73	100.00	0.39	6.60	43.96	23.44
	20.78	0.00	0.00	100.00	52.63	0.00	59.45	17.80
Very	15.22	0.00	0.00	0.00	0.00	0.00	42.57	34.83
	13.03	0.00	0.00	0.00	29.11	0.00	31.09	32.95
Cannot	8.34	0.00	0.00	0.00	0.00	0.00	13.47	41.73
	9.34	0.00	0.00	0.00	18.26	0.00	9.45	49.25
Difficulty Combing Hair								
No	72.64	100.00	100.00	100.00	100.00	100.00	0.00	0.00
	71.52	100.00	100.00	100.00	0.00	100.00	0.00	0.00
Some	15.76	0.00	0.00	0.00	0.00	0.00	72.71	35.79
	16.05	0.00	0.00	0.00	75.70	0.00	81.59	23.61
Very	7.67	0.00	0.00	0.00	0.00	0.00	27.29	29.08
	6.72	0.00	0.00	0.00	24.30	0.00	18.41	27.84
Cannot	3.93	0.00	0.00	0.00	0.00	0.00	0.00	35.13
	5.71	0.00	0.00	0.00	0.00	0.00	0.00	48.54
Difficulty Washing Hair								
No	57.93	100.00	76.90	0.00	93.77	76.68	0.00	0.00
	55.77	100.00	100.00	0.00	0.00	100.00	0.00	0.00
Some	15.23	0.00	23.10	0.00	3.75	1.75	61.35	0.10
	13.83	0.00	0.00	0.00	30.34	0.00	65.37	0.00
Very	10.07	0.00	0.00	0.00	2.48	6.46	38.65	11.35
	9.31	0.00	0.00	0.00	21.91	0.00	34.63	7.52
Cannot	16.77	0.00	0.00	0.00	0.00	0.00	0.00	88.55
	21.09	0.00	0.00	0.00	47.76	0.00	0.00	92.48
Difficulty Grasping Small Objects								
No	65.97	100.00	89.39	42.80	100.00	100.00	0.00	12.58
	65.38	100.00	100.00	79.18	0.00	100.00	0.00	6.32
Some	20.51	0.00	10.61	57.20	0.00	0.00	65.67	31.56
	20.77	0.00	0.00	20.82	59.06	0.00	75.58	26.95
Very	10.66	0.00	0.00	0.00	0.00	0.00	32.87	33.69
	9.82	0.00	0.00	0.00	31.08	0.00	24.42	33.91
Cannot	2.85	0.00	0.00	0.00	0.00	0.00	1.45	22.17
	4.04	0.00	0.00	0.00	9.86	0.00	0.00	32.82
See Well Enough to	76.01	100.00	100.00	100.00	100.00	0.00	100.00	49.75
Read Newspaper	72.17	100.00	100.00	100.00	100.00	0.00	100.00	36.26
Table 1 (cont'd)								
Subject Health								
Excellent	12.96	26.71	10.07	0.00	22.64	1.74	0.00	0.00
	13.18	28.50	16.05	0.00	0.00	1.78	0.00	2.46
Good	32.38	54.02	4.85	0.00	47.64	52.30	0.00	8.67
	32.34	53.88	48.17	0.00	8.94	59.30	3.13	8.23
Fair	34.09	19.26	43.06	49.28	29.73	22.23	58.64	20.12
	33.16	17.63	33.82	49.34	3.08	25.92	66.45	22.29
Poor	20.58	0.00	0.00	50.72	0.00	6.73	41.36	71.21
	21.33	0.00	1.95	50.66	59.98	0.00	30.42	67.01
Rheumatism Arthritis	76.02	62.36	100.00	100.00	62.23	23.94	100.00	74.99
	74.10	58.20	100.00	100.00	68.91	23.32	100.00	64.04
Paralysis	7.82	0.00	14.41	0.00	0.00	0.00	0.67	45.39
	8.25	0.00	13.40	0.00	0.00	0.00	0.00	52.03
Permanent Stiffness	25.20	6.75	27.93	100.00	0.00	0.00	50.12	36.60
	22.84	3.49	16.54	97.69	2.80	1.96	48.99	28.87
Multiple Sclerosis	0.55	0.00	1.88	0.00	0.00	0.00	0.00	2.07
	0.65	0.00	0.40	8.40	0.00	0.00	0.00	1.37
Cerebral Palsy	0.41	0.11	0.00	4.70	0.00	0.00	0.00	1.19
	0.33	0.02	0.00	1.69	0.00	0.45	0.00	1.69
Epilepsy	0.67	0.00	0.00	6.47	0.93	0.00	0.00	2.15
	0.81	0.00	0.00	5.75	1.60	0.00	0.00	3.19
Parkinson's	2.27	0.00	0.00	8.45	5.41	2.50	0.00	9.14
	2.70	0.00	0.00	15.81	9.63	0.00	0.00	8.39
Glaucoma	8.46	0.00	0.00	0.00	0.00	68.34	0.00	4.66
	9.68	0.00	0.00	0.00	0.00	72.71	0.00	5.41
Diabetes	16.07	0.00	0.00	0.00	0.00	0.00	70.83	27.09
	16.43	0.00	0.00	0.00	0.00	0.00	69.42	29.24
Cancer	4.07	0.00	0.00	68.03	0.00	0.00	0.00	0.00
	5.28	0.00	0.00	76.86	9.06	0.00	0.00	2.92
Constipation	32.76	9.23	5.40	100.00	6.55	25.90	83.99	55.47
	31.59	6.21	2.31	100.00	44.65	18.42	82.65	44.10
Trouble Sleeping	41.97	13.60	8.34	100.00	0.66	5.38	100.00	45.88
	38.31	5.67	3.75	100.00	31.26	0.00	100.00	30.00
Headache	18.39	0.00	0.00	100.00	0.00	1.15	75.48	15.81
	17.10	0.00	0.00	100.00	0.00	0.00	63.11	9.79
Obesity	27.38	25.30	36.80	0.00	0.00	0.00	70.49	15.34
	24.13	23.01	31.28	0.00	0.00	0.00	74.65	10.14
Arteriosclerosis	28.79	0.00	0.00	100.00	2.45	45.45	58.58	48.65
	29.01	0.00	0.00	100.00	58.49	23.70	52.82	47.47
Mental Retardation	1.43	0.00	0.00	0.00	0.00	8.02	0.00	5.86
	1.58	0.00	0.00	0.00	0.26	8.16	0.00	6.56
Senility	6.00	0.00	0.00	0.00	0.00	31.63	0.00	32.53
	8.25	0.00	0.00	0.00	22.63	35.17	0.00	36.06
Heart Attack	5.62	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	5.21	0.00	0.00	83.63	11.19	0.00	0.00	0.00
Other Heart Problem	28.05	0.00	0.00	100.00	0.00	5.86	93.46	26.88
	30.32	0.00	0.00	100.00	52.59	0.00	91.33	19.12
Hypertension	48.68	36.73	42.01	24.72	25.25	0.23	100.00	51.28
	44.95	33.83	32.49	28.97	33.37	0.00	100.00	44.57
Stroke	5.26	0.00	0.00	29.94	0.00	4.41	0.00	25.98
	5.81	0.00	0.00	0.00	35.77	0.00	0.00	21.89
Circulation Trouble	52.51	14.87	36.10	100.00	6.40	13.40	100.00	76.60
	50.41	12.46	14.38	100.00	90.69	0.00	100.00	74.88
Pneumonia	5.14	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	5.19	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Bronchitis	13.96	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	12.55	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Influenza and Other	18.08	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Flu-Like Symptoms	16.57	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Emphysema	9.61	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	9.71	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Asthma	7.94	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	7.22	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Broken Hip	2.10	0.00	11.35	0.00	0.00	0.00	0.00	2.71
	1.29	0.00	3.30	0.00	5.48	0.00	0.00	2.17
Other Broken Bones	5.05	1.83	13.87	35.04	0.00	0.00	0.00	4.35
	4.57	0.00	0.00	29.68	22.08	0.00	4.77	1.75

Table 2: Regression Results for Adjusted Weights as Functions of the Grade of Membership

Model	F(6, 4175)	0-value	R2
Cross-sectional weight 1982	2.52	0.02	0.004
Cross-sectional weight 1984	1.65	0.13	0.002
Longitudinal weights 1982-1984	6.29	<0.001	0.009