

U.S. Department of Health and Human Services Assistant Secretary for Planning and Evaluation Office of Disability, Aging and Long-Term Care Policy

SMALL AREA ESTIMATION OF DEPENDENCY:

FINAL REPORT

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ABSTRACT

Health planning efforts for the elderly have been hampered by the lack of reliable estimates of the noninstitutionalized long-term care population. Until recently national estimates were virtually nonexistent, and reliable local estimates remain unavailable. With the recent publication of several national surveys, however, synthetic estimates can be made for states and counties by using multivariate methods to model functional dependency at the national level, and then applying the predicted probability to corresponding state and county demographic and contextual data. Using the 1984 National Health Interview Survey's Supplement on Aging and the 1986 Area Health Resources File System, we produced log-linear regression models that included demographic and contextual variables as predictors of functional dependency among the noninstitutionalized elderly. We found race, sex, age, and the percent of the elderly population in the community who reside in poverty to be significant predictors of functional dependency. Applying these models to 1986 Medicare Enrollment Statistics we produced estimates of two levels of functional dependency for all states and a sample of counties. While a substantial portion of long-term care planning occurs at the state and local level, many of the rigorous and authoritative population surveys provide prevalence data on the community-based long-term care population which is reliable only for national estimates. Health planning efforts for the elderly have been hampered by the lack of reliable data for making population-based estimates at subnational levels.

This paper presents log-linear regression models that can be used to produce regression-adjusted synthetic estimates of the elderly community-based long-term care population. We present state estimates, as well as estimates for a sample of counties.

PREVIOUS RESEARCH

Defining the Community-Based Long-Term Care Population

A primary goal in defining the long-term care population is developing a definition that can easily be translated into service and manpower estimates. To the extent feasible, it also should be compatible with available data and measures. Such estimates can then be translated into expenditure estimates for purposes of budgeting and health planning.

One approach, counting the number of people with chronic conditions, provides an informative but not entirely satisfactory estimate of service needs because many conditions have few, if any, consequences for health care utilization behavior (Haber 1971 and 1973).

Inventories of the number of people who report limitations in their usual activity are also an informative measure for some epidemiological purposes. But "usual activity" varies with age, occupation, work-force participation, and self-perceived role. This variation raises some questions concerning validity and reliability of the concept when used as a survey item with a retired population.

Similarly, a National Health Interview Survey item that asks whether or not an individual stays in bed most days because of a chronic condition has somewhat limited consequence for manpower-need estimates. This is so because it is not clear that human intervention would alter those individuals' conditions. In addition, they are a very small group; in 1980, only 17,000 nondependent persons, or less than one-tenth of 1% of the aged population, reported staying in bed most days due to a chronic condition (Weissert 1985).

The notion of functional disability as the criterion for inclusion in the long-term care population comes closer to the mark by focusing on an individual's ability to perform basic functions. Need for human help in daily functioning has direct implications for manpower estimates and long-term care expenditure projections. Nonetheless, even this measure is not problem free. Definitions of functional disability vary in the nature of the functional disabilities included as well as the degree of impairment. Definitions also differ by the duration of the disability, although most people accept the 1957 distinction offered by the Commission on Chronic Illness that care is long-term when it lasts more than 90 days.

For purposes of this paper, we have chosen to estimate functional dependency as it is most commonly defined by long-term care researchers. That is, dependency in activities of daily living (ADL), mobility, and instrumental activities of daily living (IADL). These measures repeatedly have been shown to be reliable and valid in helping to identify problems that require treatment or care, and they are readily available in a number of comprehensive assessment and information systems (Katz 1983), including several national surveys.

This is not to say that they are the only measures of the need for long-term care that might have been used. Other reliable measures of an elderly person's ability to perform physical functions include the Barthel Index, which includes a measure of muscle strength among other subscales; the Kenney Self-Care Evaluation, which includes additional measures of personal hygiene not measured by the Katz scale; and many others (Kane and Kane 1981). Few of these scales and measures have been widely used in national surveys, however, despite their potential to yield considerable additional detail on the elderly population's need for care.

Prevalence of Functional Dependency

Using surveys conducted at both the national and local level, numerous estimates of the prevalence of functional dependency among the elderly population have been made. Nagi (1976), using a 1972 probability sample of the continental United States, found that almost 17% of the noninstitutionalized elderly population required assistance with mobility or personal care. Estimates from the 1979 and 1980 National Health Interview Surveys (NHIS) indicate that almost 12% of the noninstitutionalized elderly, or 2.8 million elderly, were dependent in personal care, mobility, household activities, or home administered health care services (Feller 1983; Weissert 1985). Using data from the 1982 National Long-term Care Survey (NLTCS), Macken (1986) reported that 19% or 5 million Medicare enrollees were functionally impaired. Similar estimates were reported by Manton and Soldo (1985) who found 4.6 million disabled elderly using data from the 1982 NLTCS. Dawson, Hendershot and Fulton (1987), using the 1984 NHIS's Supplement on Aging, found that 10% of the elderly population received help performing personal care activities, and almost 22% were receiving help with home management activities. The variations in prevalence estimates by these investigators reflects the wide, variety of definitions, samples and levels of aggregation used by them.

In addition to national estimates, surveys of functional dependency also have been conducted at the subnational level. Notable among these are the Duke Longitudinal Studies of Aging (1955-1976 and 1975-1984), the Manitoba Longitudinal Study on Aging (1970-1977), the Duke OARS Survey (1972-1974), the Massachusetts Health Care Panel Study (1974-1980), the Cleveland OARS General Accounting Office Study (1975-1986), and the Framingham Disability Study (1976-1978).

Correlates of Functional Dependency

In addition to prevalence estimates obtained from population based surveys, researchers have explored the demographic, health status and other factors which typically accompany functional decline. A number of specific correlates of dependency

have been suggested in previous work. Among these, increases in physical disability have been significantly associated most often with advanced age (Shanas 1962 and 1968; Jette and Branch 1981; Feller 1983; Branch, Katz, Kniepmann and Papsidero 1984; Manton and Soldo 1985; Palmore, Nowlin and Wang 1985; Weissert 1985; Macken 1986; Dawson, Hendershot and Fulton 1987), and with being female (Shanas 1962 and 1968; Jette and Branch 1981; Branch et al. 1984; Palmore, Nowlin and Wang 1985; Manton and Soldo 1985; Weissert 1985; Manton 1988). However, Feller (1983) found no significant difference in rates of dependency by gender, and Dawson, Hendershot and Fulton (1987) found gender differences to disappear when age structure was taken into account.

Other correlates of decrement in functional ability which have been noted, include being nonwhite (Palmore, Nowlin and Wang 1985; Macken 1986), unmarried or residing with family members (Shanas 1962 and 1968; Palmore, Nowlin and Wang 1985), having a low income (Shanas 1968; Palmore, Nowlin and Wang 1985), and being at the low end of the social class continuum (Shanas 1968)

Most recently Jette and Branch (1985) found living alone to be the strongest correlate of physical disability. While they found advancing age to be related to disability among those who live alone, no relationship between advanced age and disability was found among those who lived with others. They also found men who live with others more likely to report physical disability compared to women, but found no significant gender differences among those who live alone. Among those who lived with others, level of income was inversely related to increasing disability.

In a study of active life expectancy (years free of physical disability), using data from a 1974 Massachusetts health care panel study of noninstitutionalized elderly, Katz et al. (1983) found active life expectancy to decrease with age, and to be shorter for the poor at all ages.

A few researchers have also investigated the relationship of functional dependency to other factors with the use of multivariate methods. Nagi (1976) found physical performance, age, number of conditions, sex, race, emotional performance and health status to explain over 74% of the variation in the dependent variable, independent living. In a longitudinal study using residual analysis Palmore, Nowlin and Wang (1985) found changes in ADL abilities to be predicted by prior ADL abilities, age and physical ratings. Using AID (Automatic Interaction Detection) analysis, Heinemann (1985) found the number of chronic conditions, age, social class, and income to be significant predictors of health decline. Pinsky, Leaverton and Stokes (1987) found younger age and higher education levels to be significant predictors of good functioning among both men and women. Using a split-halves test on a data file created by the merger of the 1977 National Nursing Home Survey and the 1977, 1979, and 1980 National Home Health Survey, Unger and Weissert (1988) found that a model with age and age-squared accurately produced regression-adjusted synthetic estimates of the prevalence of dependency among the noninstitutionalized elderly population.

Synthetic Estimation

Although several methods exist to produce synthetic estimates none has been found to be uniformly superior. One well suited method uses a fitted regression model to predict quantitative characteristics of the area of interest. The dependent variable in such a model is the characteristic for which the small area estimate is to be obtained (dependency) while the explanatory variables are predictors available externally to the estimation process (e.g, age, sex, race, income, marital status, or living arrangement).

This approach has been widely used. The first detailed conceptual and empirical basis for the use of regression models for estimating population size was presented by Erickson (1973, 1974). Methods developed by Kalsbeek (1973) and Cohen et al. (1977) extended this idea. Gonzalez and Hoza (1978) applied Ericksen's regression method to the estimation of unemployment for selected Standard Metropolitan Areas, while Nicholls (1977) followed the regression method in estimating population sizes for Statistical Divisions in Queensland, Australia. Levy (1979) evaluated a regressionadjusted synthetic estimator. Royall (1977) introduced the prediction approach to small area estimation based on an assumed regression model. Holt (1979) and Laake (1979) have subsequently extended this prediction approach under several basic population models. DiGaetano and associates (1980) used synthetic and regression procedures to produce estimates at local levels using NHIS data. Heeringa (1982) examined the roles that a model may play in small area estimation based on sample survey data sets and discussed current perceptions of the strength and weaknesses of model-based small area estimation methods. Diffendal and colleagues (1983) used the synthetic and regression methods for small area adjustment methodologies applied to the 1980 Census. Unger and Weissert (1988), as previously noted, developed a regressionbased technique for estimating state-level estimates of functionally dependent elderly.

METHODOLOGY

Data Sources

In the current analysis, data were drawn from the 1984 National Health Interview Survey's Supplement on Aging (1984 NHIS-SOA), the 1986 Area Resource File System (ARF), and 1986 Medicare Enrollment Statistics.

The 1984 NHIS-SOA is a multistage area probability sample which provides selfreported characteristics for 11,497 civilian noninstitutionalized elderly (age 65 and over). It includes information on their family structure, living arrangement, social support, conditions and impairments, functional abilities (ADL and IADL), and other healthrelated and social information.

To develop the regression models, contextual variables from the ARF were attached to individuals on the NHIS-SOA using geographic markers. The ARF is a compilation of county and other geographic area statistics concerning a wide range of health planning related variables drawn from a multitude of survey sources. Using the geographic identifiers available on the 1984 NHIS-SOA, corresponding community data were attached at the Standard Metropolitan Statistical Area (SMSA) for individuals residing in one of 31 large self-representing SMSAs. Individuals on the data set who resided outside these 31 areas were assigned the corresponding regional (northeast, north central, south or west) and urbanity (SMSA or nonSMSA) average for their type of residence. The result was 39 distinct geographic areas: 31 self-representing SMSAs, and 4 urban and 4 nonurban regional areas.

To generate regression-adjusted synthetic estimates of the functionally dependent elderly population in an area, rates of dependency produced by the model on national data must be multiplied by population data from small areas. Any explanatory variable included in the national model must also be available in the small area population data. As intercensal age, sex and race specific population data for the elderly are not readily available in small age increments at the small area level, we used Medicare Enrollment data for our estimates. Necessary adjustments to the Medicare data to account for nonenrollment among the elderly, and for the proportion of the elderly residing in nursing homes are discussed later in the report.

MODEL SPECIFICATION

Unit of Analysis

The unit of analysis for this study was the individual elderly person who was a respondent to the 1984 NHIS-SOA. Although the weighted sample size of the 1984 NHIS-SOA is over 26 million, so as not to exaggerate significance levels in model evaluation, we normalized the provided survey weight variable to sum to the actual sample size of 11,497.

Dependent Variable

The dependent variable for our analysis was a three level hierarchical measure which differentiated those who were dependent in activities of daily living (ADL), those who were dependent in mobility or instrumental activities of daily living (IADL), and those who were not dependent in either. Individuals were classified into their highest level of dependency defined as follows:

- ADL DEPENDENT: Elderly individuals residing in the community, who, because of a health or physical problem, reported that at the time of the survey they had difficulty with and received human assistance with eating, transferring, toileting, dressing or bathing.
- MOBILITY/IADL DEPENDENT: Elderly individuals residing in the community, who at the time of the survey were not ADL dependent, but because of a health or physical problem reported difficulty with and received human assistance with inside mobility, outside mobility, meal preparation, grocery shopping, money management, housework (light and heavy) or telephone usage.
- INDEPENDENT: Elderly individuals residing in the community who at the time of the survey were neither ADL nor IADL dependent.

Given the construction of the 1984 NHIS-SOA, it had to be assumed that an individual who received help or supervision with any ADL or Mobility/IADL item was actually in need of such assistance. In addition, incontinence, though not mentioned in the above definition, was captured by other ADL measures. That is, we elected to exclude from our definition of ADL dependency individuals who were suffering from stress incontinence only. These are individuals who, though incontinent, do not require human assistance, nor report the need for assistance, in any one of the other five ADLs. Such individuals have no bearing on manpower estimates. Those who were incontinent and did need help were included in the ADL definition by virtue of needing help in one or more of the remaining ADL functions, e.g. dressing.

Explanatory Variables

Based upon the literature review and previous work done by Weissert, the following variables were expected to influence the prevalence of dependency among the noninstitutionalized elderly population:

- Demographic characteristics of the aged individual--measured by age, gender, race, marital status and living arrangement;
- Socio-economic characteristics of the aged individual--measured by education and income;
- Contextual characteristics of the elderly individual's community--measured by the supply of physicians, hospital beds, and nursing home beds; Medicaid nursing home eligibility policies; area mortality rates; urbanity; and climate.

Of course, the choice of predictor variables was limited to variables available on the merged 1984 NHIS-SOA/ARF data set and for which population distributions could be obtained for states and counties. Coupling the constraints of the merged data set and Medicare data, the following variable definitions were available for use:

- Sex--male and female (coded 1 if female and 0 if male);
- Race--white and nonwhite (coded 1 if nonwhite and 0 if white);
- Age Group--age in 5 year intervals from 65 to 85 and over (coded as a zero-centered variable equal to the youngest age in the five year interval minus 75, divided by 5, i.e. -2, -1, 0, 1, or 2);
- **Age-Squared**--a quadratic of the "age group" variable (coded as the square of the "age group" variable, i.e. 4, 1, 0, 1 or 4); and
- Interactions--pairwise combinations of all of the above (coded as the product of the pair).

In addition to these variables a number of contextual variables were hypothesized to affect the rate of functional dependency among the noninstitutionalized elderly. For the functionally dependent, residency in the community versus residency in hospitals or nursing homes is determined in part by access to nursing home beds (Weissert and Cready in press), and perhaps also by the supply of hospital beds, which sometimes serve as a substitute for nursing home beds (Weissert and Cready 1988). Income also is believed to enhance access to nursing homes (Scanlon 1980a; Scanlon 1980b).

The supply of physicians and Medicaid eligibility policies, both of which may enhance an individual's access to nursing homes and hospitals, may further affect rates of institutionalization among the functionally dependent.

Mortality rates are reflective of the health status of the elderly population. Measures of urbanity also are reflective of health status in as much as dwellers of urban areas face different threats to mortality and morbidity than residents of rural areas. In addition, urbanity is also a proxy for available health care options--both acute and long-term care--as well as available social supports, and as such may affect rates of institutionalization. Contextual variables available for inclusion in our model after merging the ARF and the 1984 NHIS-SOA included:

- the number of nursing home beds per 1000 elderly;
- the number of unoccupied nursing home beds per 1000 elderly;
- the number of acute care hospital beds per 1000 elderly;
- the per capita income of the population;
- the percent of the elderly who reside in poverty;
- the number of primary care physicians per 1000 elderly;
- the percent of the poverty population that is covered by Medicaid;
- the age-adjusted mortality rate;
- the number of heating degree days;
- the population per square mile;
- the elderly population per square mile; and
- the percent of the population that resides in an urban area.

The contextual variables were entered into our models as both continuous and categorical variables. For the categorical analysis the variables were collapsed into three levels: high, medium and low. To collapse the community variables they first were arrayed in descending order by size. Then using the upper and lower quartiles as starting points, breaks were set at the point in the array where large differences between two consecutive values existed and where consistency with substantive meaning applied.

ANALYSIS

Statistical Package

The dependent variable necessitated the use of a statistical procedure that accounted for its three levels. As the variable is theoretically ordered, it seemed logical to consider using an ordered method. The use of ordered logistic regression, a method commonly used in such situations and one that corresponds to a proportional odds ratio model, therefore was evaluated. However, the structure such a model imposes on the data was found to be inappropriate. This was learned by estimating two logistic component equations: ADL or IADL dependent verses no dependency; and ADL dependent verses IADL or no dependency. While the parameter estimates for race, age, and age-squared were similar for each of the two component models and thereby compatible with the proportional odds model, the parameter estimates for sex contradicted it by differing by almost 19 fold. Thus, the proportional odds ratio model imposed by logistic regression was considered inappropriate for modelling our dependent variable.

Instead a multicategory extension of logistic regression which provides a more general structure was used. The log-linear model was fit using a SAS supported procedure designed for categorical data modeling, PROC CATMOD. For log-linear model analysis CATMOD uses maximum likelihood estimation. Given the three category dependent variable, two sets of parameter estimates were produced: one for the logged ratio of not dependent to ADL dependent, and one for the logged ratio of IADL dependent to ADL dependent. Working with these two equations simultaneously yielded a formula for each category of the dependent variable: (1) not dependent; (2) IADL dependent; and (3) ADL dependent. (See Appendix A.)

Design Effects

The CATMOD procedure, however, cannot be used with a statistical package that accounts for the complex sampling design of the 1984 NHIS-SOA. Without accounting for sampling design effects, inaccurate variance estimates and significance levels may result. Experience shows that without accounting for such complexity, the variances of the regression coefficients produced in general are likely to be underestimated on the order of 5-20%.

To gauge the magnitude of the sample design effects in this analysis, results from the SAS procedure PROC LOGIST were compared with the results from the PROC RTILOGIT procedure (Shah et al. 1984), a SAS supported logistic regression package developed specifically to account for complex sample designs when calculating variances and significance levels. Because RTILOGIT has the ability to account for only a two level dependent variable, for comparative purposes, a model for ADL dependent verses not dependent was fit. To calculate the design effects, the variances produced with the PROC RTILOGIT procedure were divided by the variances produced with the PROC LOGIST procedure. The results showed that design effects were relatively small (i.e. less than 1.2) for all the parameters of interest (i.e. age, sex, race, and age-squared). Since adjustment of the chi-square statistics produced from CATMOD by division by the design effects would not influence the clear significance of the parameters in our model, there was not a problem with the use of the CATMOD procedure; i.e., the slightly larger variance estimates likely to be produced by complex sample methods such as RTILOGIT would not alter results or conclusions.

For model testing, the database was randomly divided in half within each primary sampling unit. In the first half of the database candidate models were fit for the dependent variable. Once model development was completed, the goodness-of-fit of the model was validated in the other half of the database by three methods. First the model was run in the other half of the data set, and the goodness-of-fit of the model was evaluated with the chi-square statistics associated with the individual parameters and with the lack-of-fit statistic. As the parameter estimates remained significant (p<.001), and the lack of fit statistic remained nonsignificant (p>.25) the structure of the model appeared to fit the data quite well.

In addition, the model was run on the entire sample to test the fit of the estimated coefficients. This was done by including an indicator variable representing the half of the data set from which each observation came, as well as all of its pairwise interactions. As the parameter estimates for the indicator and each of its interactions, were non-significant (p>.25) in an overall test, goodness-of-fit of the model was supported.

Third, the goodness-of-fit of the model was evaluated by comparing the similarity of the model-predicted dependency rates with their observed counterparts in the other half of the data set. In so doing, the candidate models were used to determine the predicted values of the probability of dependence for individuals in the other half of the database. The differences between these predicted values and their true value gives a residual value for that individual. The closeness of the averages of the residuals to zero for various subgroups of individuals (e.g. males, females, different age groups, etc.) and their lack of correlation of the residuals with characteristics of individuals are indicative of goodness-of-fit. In almost all cases (28 out of 30) the t-statistic indicated that the mean value of the residuals for each of the subgroups was not significantly (p>.05) different from 0. In addition, Pearson correlations were evaluated for the residuals and each of the explanatory variables, and their low values supported the fit of the model.

RESULTS

Direct Estimates

Direct estimates from the 1984 NHIS-SOA indicate that approximately 2.0 million (or 7.3%) of the noninstitutionalized elderly Americans suffered from at least one ADL dependency, and an additional 4.2 million (or 16.4%) suffered from at least one IADL dependency. Prevalence and percentage estimates by race, sex and age are shown in Table 1 and Table 2, respectively.

With the use of the primary sampling unit (PSU) and the primary strata used for sampling, we calculated standard errors using a statistical package (PROC SESUDAAN) which accounts for the complex sampling design of the 1984 NHIS-SOA (Shah 1981). The standard errors were computed using the first-order Taylor approximation of the deviations of estimates from their expected values and are presented in Table 3 and Table 4.

Regression-Adjusted Results

A model including demographic and contextual variables was fit to the dependent variable, functional dependency. Table 5 presents the survey-weighted results of the log-linear regression analysis. Race, sex, age, age-squared and the categorical variable reflecting the percent of the elderly (65 and older) population who reside in poverty were significant (p<.001) predictors of functional dependency in the overall model. Assuming a true log-linear relationship, the continuous form of the contextual variable (percent elderly population in poverty) statistically would be preferable. However, as we found negligible statistical differences between the continuous and the categorical use of the contextual variable, and as we felt results and examples could more easily be presented with the categorical variable, our results focus on the latter. (Survey-weighted results for the continuous variable are presented in Table 6.)

In our analysis we found that three additional contextual variables (both in their continuous and categorical forms) were significant predictors of functional dependency: the number of heating degree days (a variable reflective of climate and a proxy for geographic region); the ratio of Medicaid recipients to the population below poverty (a measure of access to health care services); and the number of unoccupied nursing home beds per 1000 elderly (a measure of the supply of beds relative to the demand for them). When each of these variables was added to the model with race, sex, age, and age-squared each was significant (p<.02). However, when more than one of the community variables was included in the model, only the poverty variable remained significant (p<.10).

The fit of the model which included the categorical poverty variable as the only contextual variable was evaluated with the log-likelihood ratio chi-square statistic. Since the statistic was nonsignificant, the use of the model was supported. The need for pairwise interactions of the variables was evaluated and determined to be unnecessary.

Further evaluation of the fit of the model was done by plotting the observed agespecific rates of dependency and the regression-predicted rates of dependency. As can be seen from Figure 1 and Figure 2, the predicted rate of both ADL (Figure 1) and IADL (Figure 2) dependency closely approximate the observed rates. However, when the population is divided into smaller subgroups, such as nonwhite females, the model fits somewhat less well (Figure 3).

Table 7 presents the regression-adjusted estimates of the prevalence of ADL dependency and Table 8 of IADL dependency. As the poverty variable has 3 values (less than 8%, between 8 and 15%, and over 15% of the elderly population residing in poverty), 3 sets of estimates are produced--one for communities with low rates of poverty, one for communities with moderate rates, and one for communities with high rates of poverty among the elderly. As can be seen in the tables, results showed the likelihood of ADL and IADL dependency increases quadratically with age, and also increases with being nonwhite, and with an increasing percent of the elderly population residing in poverty. The likelihood of IADL dependency also increases with being female, but the likelihood of being ADL dependent does not increase uniformly with being female. Although the likelihood of being ADL dependent is in general higher for females than males until age 80 in communities of low and moderate levels of poverty, and until age 75 for those in high poverty communities, after these ages the percent of noninstitutionalized males with an ADL impairment is either equal to or greater than that of females.

Regression-Adjusted Synthetic Estimates

Percentages generated with the regression models can be multiplied by corresponding population estimates for specific geographic areas of interest to generate estimates of the number of noninstitutionalized functionally dependent elderly in a given community. Population subgroups, of course, are defined by the explanatory variables included in the model.

As mentioned earlier, as intercensal data are not readily available for the elderly population in small age intervals by race and sex for small areas, we elected to use Medicare Enrollment data for the production of our estimates. Although Medicare data, given its level of detail and recency, are the best available data for our purposes, two adjustments had to be made to it prior to estimation.

First, only 95% of elderly Americans are enrolled in Medicare, thus requiring that we inflate the numbers to be reflective of the total elderly population. As the percent enrolled varies little across sex or family income groups, but does differ across race

groups (Ries 1987) adjustments were made which accounted for the race difference. Specifically, the number of white elderly Medicare enrollees was inflated by 4.4%, and the number of nonwhite elderly enrollees was inflated by 13.5%.

Second, because Medicare Enrollment data includes both the noninstitutionalized and institutionalized elderly population, and rates produced with the combined data set (1984 NHIS-SOA and ARF) are applicable for the noninstitutionalized population only, an adjustment had to be made to the data prior to producing the synthetic estimates. The adjustment entailed subtracting the estimated number of institutionalized elderly from the total population in a community. Using the 1985 National Nursing Home Survey and the 1985 National Health Interview Survey, a logistic regression equation was produced to estimate rates of institutionalization among the elderly population at the national level. Candidate explanatory variables for inclusion in the model included those variables available on the merged data set for which corresponding population data existed. Given this constraint, age (in five year intervals from 65 to 85 and over), sex, race (white and nonwhite), and geographic region (northeast, north central, south, and west), as well as their pairwise interactions and transformations were available for use. Region was included in the model as the supply of nursing home beds, and thus rates of institutionalization, are known to vary geographically. The model found to best fit the data included age, age-squared, sex and an indicator variable reflecting whether or not the individual resided in the north central region of the country. Appendix B presents results of the logistic model. Estimates produced from this model were used to deflate the state and county population data to be representative of the noninstitutionalized elderly population.

By applying the rates of dependency generated by the log-linear regression model (which included race, sex, age, age-squared, and the percent of the elderly who reside in poverty) to the adjusted Medicare data, we produced estimates for each state, and the largest county in each state (Table 9 and Table 10).

These estimates are based upon three assumptions. First that the race, sex, age, and poverty-specific disability rates from the 1984 NHIS-SOA did not change between 1984 and 1986. Second, that the relationship between dependency and race, sex, age, and the percent of the elderly residing in poverty is the same for a small area as it is for national averages. And third, that race, sex, age, and the percent of the elderly residing in poverty are the only important predictors of functional dependency. Thus, the estimates will err to the extent that the relationship between dependency and race, sex, age, and poverty in a community have changed over time; to the extent that the relationships vary from national averages; and to the extent to which other known or unknown factors which are not in the model strongly influence functional dependency. The latter two reflect phenomena which could occur due to variations in the health of the local aged population from national norms. For example, estimates produced would likely underestimate the prevalence of functional dependency in a community where some disabling disease was highly prevalent, but overestimate the prevalence in a community such as Miami, where there is a large concentration of well elderly.

DISCUSSION

The variables found to be significant correlates of functional dependency suggest some interesting implications. They confirm the strong relationship reported by other researchers between dependency and age, as well as the variation in age-specific rates of dependency between men and women, and whites and nonwhites. Explication of the underlying determinants of these variations are beyond the scope of this paper but reconfirming their importance suggests the need for policies and research agendas sensitive to these relationships and variations. Of particular importance is the quadratic relationship between age and dependency, meaning that with each passing five year interval rates of dependency increase at an increasing rate--a sobering prospect given the rapid expansion of the oldest old population.

Introduction of a contextual variable into the multivariate regression model may be unique in this analysis but appears overdue. The results here, which are consistent with other researchers' work, suggest that just as poverty is a strong correlate of many unwanted problems in youth and adulthood, so, too, its sequela are present in old age, manifesting themselves as higher dependency rates. Poverty rates among the elderly are known to correlate with a number of important health care system variables including the nursing home bed supply and use rates, Medicaid generosity, and the poor population's life styles, educational levels and occupational experiences.

The estimates produced here are likely to be most useful as initial building blocks for estimating long-term care service demand. A major barrier to cost-effective home and community care has been poor estimates of the rates of enrollment in such programs. Often, the result has been lower-than-expected attendance and, consequently, higher unit costs associated with operating below capacity. While functional dependency estimates at the small area level will not translate directly to demand for service, previous research has shown that utilization of health care services is closely related to need (Andersen et al. 1983; Hulka and Wheat 1985). They may also enhance understanding of some of the variation in the supply of long-term institutional care settings from region to region, state to state, and county to county. While many of the determinants of variation in both demand and supply are likely to defy measurement, either because they are stochastic (e.g. disease onset) or they are difficult to measure (e.g. political preferences of legislators and regulators in the case of supply), "need" estimates provide a useful starting point for planning.

Finally, it should be noted that while the data support the use of these equations to produce estimates of functional dependency among the noninstitutionalized elderly population, the quality of the small area estimates produced by them still needs to be evaluated in future research.

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TABL	TABLE 1: Direct Point Estimate of Noninstitutionalized Americans Aged 65 and Over Who Were Functionally Dependent in 1984													
by Age, Sex and Race														
			F	Personal Car	e Dependent	1 1			Mobility o	or Househol	d Activity De	pendent ²		
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over	65-69	70-74	75-79	80-84	85 & Over	65 & Over	
White	Male	164,644	143,520	147,240	87,750	111,319	654,473	255,589	238,009	185,456	121,775	114,223	915,052	
	Female	157,176	190,273	192,626	234,942	286,274	1,061,291	608,833	629,901	668,388	479,112	422,742	2,808,976	
	Both	321,820	333,793	339,866	322,692	397,593	1,715,764	864,422	867,910	853,844	600,887	536,965	3,724,028	
NonWhite	Male	20,095	15,920	27,803	17,060	12,628	93,506	34,700	35,507	12,834	12,037	6,461	101,539	
	Female	27,466	29,173	32,021	24,656	30,263	143,579	88,035	129,402	93,806	60,226	33,796	405,265	
	Both	47,561	45,093	59,824	41,716	42,891	237,085	122,735	164,909	106,640	72,263	40,257	506,804	
All Races	Male	184,739	159,440	175,043	104,810	123,947	747,979	290,289	273,516	198,290	133,812	120,684	1,016,591	
	Female	184,642	219,446	224,647	259,598	316,537	1,204,870	696,868	759,303	762,194	539,338	456,538	3,214,241	
	Both	369,381	378,886	399,690	364,408	440,484	1,952,849	987,157	1,032,819	960,484	673,150	577,220	4,230,832	

SOURCE: 1984 National Health Interview Survey's Supplement on Aging.

1. Personal Care dependent includes bathing, dressing, toileting, transferring or eating. Individuals classified as personal care dependent may also be dependent in mobility or household activities but are counted only as personal care dependent.

2. Mobility or household activity includes inside mobility, outside mobility, meal preparation, grocery shopping, money management, housework (heavy and light), and telephone usage. Individuals already classified and counted in this table as personal care dependent are excluded from this category.

TA	TABLE 2: Direct Point Estimates of the Percent of Noninstitutionalized Americans Aged 65 and Over Who Were Functionally													
	Dependent in 1984 by Age, Sex and Race													
			F	Personal Car	e Dependent	t ¹			Mobility	or Househol	d Activity De	ependent ²		
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over	65-69	70-74	75-79	80-84	85 & Over	65 & Over	
White	Male	4.45	5.29	7.70	9.68	20.49	6.70	7.1	9.0	9.9	13.8	21.6	9.6	
	Female	3.46	5.08	6.63	13.44	23.55	7.50	13.7	17.1	23.5	27.9	36.1	20.3	
	Both	3.91	5.17	7.05	12.16	22.61	7.17	10.7	13.7	18.1	23.1	31.6	15.9	
NonWhite	Male	5.29	5.63	12.40	20.11	30.64	9.23	9.5	13.0	6.4	15.4	15.7	10.4	
	Female	5.87	6.39	11.51	13.00	31.38	9.65	19.7	29.5	34.3	32.3	38.1	28.3	
	Both	5.61	6.10	11.91	15.20	31.16	9.48	15.1	23.2	21.9	27.3	31.0	21.1	
All Races	Male	4.53	5.32	8.19	10.58	21.20	6.93	7.3	9.3	9.5	13.9	21.2	9.7	
	Female	3.69	5.22	7.06	13.40	24.13	7.70	14.2	18.4	24.5	28.3	36.2	21.0	
	Both	4.06	5.26	7.51	12.44	23.23	7.34	11.1	14.6	18.5	23.5	31.5	16.4	

SOURCE: 1984 National Health Interview Survey's Supplement on Aging.

1. Personal Care dependent includes bathing, dressing, toileting, transferring or eating. Individuals classified as personal care dependent may also be dependent in mobility or household activities but are counted only as personal care dependent.

2. Mobility or household activity includes inside and outside mobility, meal preparation, grocery shopping, money management, housework and laundry, or taking medications. Individuals already classified and counted in this table as personal care dependent are excluded from this category.

TABLI	TABLE 3: Standard Errors for Direct Point Estimates of Noninstitutionalized Americans Aged 65 and Over Who Were Functionally												
Dependent in 1984 by Age, Sex and Race													
			F	Personal Car	e Dependent	1			Mobility of	or Househol	d Activity De	pendent ²	
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over	65-69	70-74	75-79	80-84	85 & Over	65 & Over
White	Male	22,089	17,716	19,053	16,788	15,575	44,178	28,512	35,599	19,739	16,863	15,080	51,398
	Female	61,455	20,109	23,692	21,521	25,062	24,852	41,039	34,866	52,187	28,654	31,635	97,799
	Both	30,234	32,062	31,102	27,462	30,537	81,762	52,840	44,439	60,723	30,779	37,923	114,393
NonWhite	Male	6,615	6,695	9,789	6,726	6,028	15,914	9,992	11,011	6,021	5,462	4,759	18,232
	Female	19,032	8,025	8,729	9,101	7,743	8,847	14,699	18,944	16,384	13,098	9,883	38,966
	Both	9,418	11,479	12,331	10,894	11,248	26,045	19,473	24,630	16,333	15,095	10,408	50,672
All Races	Male	23,550	19,188	22,393	18,136	16,076	47,292	29,841	26,794	21,340	18,231	15,813	53,851
	Female	21,067	23,577	25,280	26,080	26,048	62,634	42,659	37,894	55,004	31,530	31,851	102,984
	Both	33,080	32,690	36,685	28,888	31,919	86,074	56,564	49,549	63,438	35,726	38,704	124,479

SOURCE: 1984 National Health Interview Survey's Supplement on Aging.

1. Personal Care dependent includes bathing, dressing, toileting, transferring or eating. Individuals classified as personal care dependent may also be dependent in mobility or household activities but are counted only as personal care dependent.

Mobility or household activity includes inside mobility, outside mobility, meal preparation, grocery shopping, money management, housework (heavy and light), and telephone
usage. Individuals already classified and counted in this table as personal care dependent are excluded from this category.

TABL	TABLE 4: Standard Errors for Direct Point Estimates of the Percent of Noninstitutionized Americans Aged 65 and Over Who Were													
Functionally Dependent in 1982 by Age, Sex and Race														
		Personal Care Dependent ¹							Mobility of	or Househol	d Activity De	ependent ²		
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over	65-69	70-74	75-79	80-84	85 & Over	65 & Over	
White	Male	0.60	0.61	0.94	1.97	2.73	0.45	0.71	0.91	0.10	0.19	2.70	0.47	
	Female	0.45	0.64	0.69	1.23	1.68	0.40	0.84	0.91	1.59	1.67	2.01	0.62	
	Both	0.37	0.48	0.59	0.98	1.48	0.31	0.58	0.65	1.16	1.23	1.75	0.41	
NonWhite	Male	1.80	2.32	4.22	6.84	11.67	1.43	2.50	3.75	2.64	6.09	9.27	1.62	
	Female	1.81	2.02	3.26	3.78	8.08	1.16	2.68	3.04	4.27	5.12	8.24	1.90	
	Both	1.23	1.61	2.23	3.48	7.06	0.91	2.09	2.69	2.70	4.32	6.48	1.52	
All Races	Male	0.58	0.60	0.98	1.96	2.66	0.43	0.67	0.87	0.97	1.79	2.62	0.45	
	Female	0.44	0.55	0.74	1.17	1.60	0.37	0.82	0.85	1.51	1.49	1.85	0.58	
	Both	0.37	0.44	0.62	0.94	1.43	0.30	0.57	0.63	1.08	1.13	1.61	0.40	

SOURCE: 1984 National Health Interview Survey's Supplement on Aging.

1. Personal Care dependent includes bathing, dressing, toileting, transferring or eating. Individuals classified as personal care dependent may also be dependent in mobility or household activities but are counted only as personal care dependent.

2. Mobility or household activity includes inside and outside mobility, meal preparation, grocery shopping, money management, housework and laundry, or taking medications. Individuals already classified and counted in this table as personal care dependent are excluded from this category.

TABLE 5: Regression Results: Demographic and Categorical Contextual Variables											
Variable	Chi-S	p-value									
Race	28.	0.001									
Sex	217	217.76 2									
Age Group	654	.65	2		0.001						
Age Group-Squared	29.	23	2		0.001						
Poverty	36.	66	2		0.001						
Intercept	1920	0.81	2		0.001						
Lack of fit chi-square = 7 Model chi-square = 959.	128.13, df = 108, <mark>j</mark> .14, df = 10, p = 0	o = 0.0906 .001									
Log	<u>Probability of b</u> Probability of b	<u>eing not depende</u> eing ADL depend	e <u>nt</u> lent								
Variable	Coefficient Standard Error Chi-Square d.f.										
Race	-0.41	0.13	12.60	1	0.001						
Sex	-0.17	0.08	4.84	1	0.028						
Age Group	-0.59	0.03	478.96	1	0.001						
Age Group-Squared	-0.11	0.02	26.03	1	0.001						
Poverty	-0.35	0.07	25.57	1	0.001						
Intercept	2.51	0.08	1030.29	1	0.001						
Log	<u>Probability of b</u> Probability of b	eing IADL dependering ADL dependering ADL dependering	<u>dent</u> lent								
Variable	Coefficient	Standard Error	Chi-Square	d.f.	p-value						
Race	-0.02	0.13	0.02	1	0.877						
Sex	0.71	0.71 0.09 62.80 1		0.001							
Age Group	-0.20	0.03	0.03 44.47 1								
Age Group-Squared	-0.07	0.02	7.23	1	0.007						
Poverty	-0.15	0.08	3.51	1	0.061						
Intercept	0.44	0.09	22.15	1	0.001						

TABLE 6: Regression Results: Demographic and Continuous Contextual Variables											
Variable	Chi-S	p-value									
Race	31.	94	2		0.001						
Sex	219	.28	2		0.001						
Age Group	652	69	2		0.001						
Age Group-Squared	28.	79	2		0.001						
Poverty	32.	19	2		0.001						
Intercept	998	.66	2		0.001						
Lack of fit chi-square = 7 Model chi-square = 956	1232.45, df = 1170 .07, df = 10, p = 0	6, p = 0.1231 .001									
Log	<u>Probability of b</u> Probability of b	<u>eing not depende</u> eing ADL depend	e <u>nt</u> lent								
Variable	Coefficient	Standard Error	p-value								
Race	-0.46	0.12	15.78	1	0.001						
Sex	-0.17	0.08	4.96	1	0.026						
Age Group	-0.59	0.03	476.88	1	0.001						
Age Group-Squared	-0.11	0.02	25.59	1	0.001						
Poverty	-0.02	0.01	12.50	1	0.001						
Intercept	2.75	0.12	492.68	1	0.001						
Log	<u>Probability of b</u> Probability of b	eing IADL depend eing ADL depend	<u>dent</u> lent								
Variable	Coefficient	Standard Error	Chi-Square	d.f.	p-value						
Race	-0.06	0.13	0.21	1	0.650						
Sex	0.71	0.09	63.09	1	0.001						
Age Group	-0.20	0.03	43.73	1	0.001						
Age Group-Squared	-0.07	0.02	7.04	1	0.008						
Poverty	0.00	0.01	0.00	1	0.971						
Intercept	0.39	0.14	7.40	1	0.007						

TABL	TABLE 7: Regression-Adjusted Estimates of the Percentage of ADL Dependent Elderly												
	Ame	ricans Living	g in the Com	munity by A	ge, Sex and	Race							
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over						
LOW POVE	ERTY COMM	UNITY											
White	Male	2.5	3.2	4.9	9.1	18.8	4.3						
	Female	2.8	3.4	5.1	9.0	17.4	5.6						
	Both	2.7	3.4	5.1	9.0	17.7	5.1						
NonWhite	Male	3.7	4.6	7.0	12.4	24.1	6.5						
	Female	3.9	4.8	7.0	11.7	21.1	6.1						
	Both	3.8	4.8	7.0	11.8	23.0	6.2						
All Races	Male	2.7	3.3	5.1	9.3	19.9	4.5						
	Female	2.9	3.6	5.3	9.3	17.5	5.6						
	Both	2.8	3.5	5.2	9.3	18.1	5.2						
MODERAT	E POVERTY	COMMUNITY	(
White	Male	3.5	4.4	6.7	12.1	23.9	6.4						
	Female	3.8	4.7	6.9	11.7	21.5	7.2						
	Both	3.7	4.6	6.8	11.8	22.2	6.9						
NonWhite	Male	5.1	6.3	9.4	16.2	29.7	7.9						
	Female	5.3	6.4	9.1	14.8	25.5	9.0						
	Both	5.2	6.4	9.3	15.3	26.4	8.5						
All Races	Male	3.7	4.6	6.9	12.4	24.0	6.5						
	Female	3.9	4.8	7.0	11.9	21.7	7.3						
	Both	3.8	4.7	6.9	12.0	22.4	7.0						
HIGH POVI	ERTY COMM	UNITY											
White	Male	4.9	6.1	9.1	15.9	29.7	8.4						
	Female	5.2	6.3	9.1	14.9	26.2	9.0						
	Both	5.1	6.2	9.1	15.3	27.3	8.8						
NonWhite	Male	7.0	8.5	12.5	20.7	35.9	11.4						
	Female	7.1	8.4	11.8	18.4	30.2	11.3						
	Both	7.1	8.5	12.0	19.0	32.3	11.3						
All Races	Male	5.2	6.4	9.7	16.4	30.6	8.9						
	Female	55	6.7	9.5	15.5	26.7	9.4						
	Both	5.3	6.6	9.6	15.8	28.0	9.2						

TABLE	TABLE 8: Regression-Adjusted Estimates of the Percentage of IADL Dependent Elderly												
	Ame	ricans Living	g in the Com	munity by A	ge, Sex and	Race	-						
Race	Sex	65-69	70-74	75-79	80-84	85 & Over	65 & Over						
LOW POVE	ERTY COMM	UNITY											
White	Male	5.2	6.6	8.9	12.5	17.3	7.3						
	Female	11.7	14.4	18.8	25.2	32.5	17.5						
	Both	8.7	11.5	14.5	22.0	29.4	13.5						
NonWhite	Male	7.5	9.3	12.3	16.7	21.7	10.3						
	Female	16.2	19.7	25.0	32.0	38.7	21.1						
	Both	12.0	17.0	17.7	29.3	27.7	16.7						
All Races	Male	5.5	6.8	9.2	12.7	18.2	7.6						
	Female	12.2	15.2	19.2	25.9	32.8	17.9						
	Both	9.1	12.2	14.7	22.7	29.2	13.8						
MODERAT	E POVERTY	COMMUNITY	(-						
White	Male	6.3	7.8	10.4	14.4	18.9	9.0						
	Female	13.8	16.9	21.7	28.2	34.8	19.9						
	Both	10.4	13.1	17.3	23.5	29.9	15.5						
NonWhite	Male	8.9	11.0	14.3	18.8	23.1	11.8						
	Female	18.9	22.7	28.2	35.0	40.4	25.2						
	Both	13.8	17.6	21.4	28.9	36.6	19.1						
All Races	Male	6.5	8.1	10.7	14.6	19.1	9.2						
	Female	14.1	17.3	22.0	28.6	35.1	20.2						
	Both	10.6	13.4	17.5	23.8	30.2	15.7						
HIGH POVI	ERTY COMM	UNITY											
White	Male	7.5	9.3	12.2	16.3	20.3	10.5						
	Female	16.2	19.6	24.7	31.1	36.5	22.1						
	Both	12.4	15.2	19.7	25.9	31.1	17.3						
NonWhite	Male	10.5	12.8	16.3	20.8	24.1	14.1						
	Female	21.7	25.8	31.4	37.6	41.3	28.3						
	Both	17.3	21.1	25.5	33.5	35.0	23.1						
All Races	Male	7.9	9.8	12.9	16.8	20.9	11.0						
	Female	17.0	20.8	25.9	32.3	37.1	23.2						
	Both	13.1	16.2	20.7	27.1	31.6	18.3						

TAE	TABLE 9: 1986 Dependent Noninstitutionalized Elderly Population by State: Regression-Adjusted Synthetic Estimates													
Chata	Elderly	Nu	Imber Depen	dent	Per	cent Depend	dent							
State	Populations	Total	ADL	IADL	Total	ADL	IADL							
California	2,685,304	521,891	147,505	374,386	19.4	5.5	13.9							
New York	2,169,180	521,526	162,389	359,137	24.0	7.5	16.6							
Florida	1,880,487	426,861	133,050	293,811	227	7.1	15.6							
Texas	1,475,817	409,903	139,822	270,081	27.38	9.5	18.3							
Pennsylvania	1,634,088	376,538	115,873	260,665	23.0	7.1	16.0							
Illinois	1,278,849	300,132	92,840	207,292	23.5	7.3	16.2							
Ohio	1,239,037	284,862	87,738	197,124	23.0	7.1	15.9							
Michigan	1,001,901	229,029	70,624	158,405	22.9	7.0	15.8							
New Jersey	935,069	215,410	66,269	149,141	23.0	7.1	15.9							
North Carolina	699,501	195,934	65,655	130,279	28.0	9.4	18.6							
Missouri	640,658	180,495	61,902	118,593	28.2	9.7	18.5							
Massachusetts	749,017	177,057	55,050	122,007	23.6	7.3	16.3							
Georgia	570,835	163,071	54,646	108,425	28.6	9.6	19.0							
Virginia	564,433	158,247	53,509	104.738	28.0	9.5	18.6							
Tennessee	551,947	154.822	52.591	102,231	28.1	9.5	18.5							
Indiana	614.558	141.704	43.800	97.904	23.1	7.1	15.9							
Wisconsin	593,261	136,679	42,885	93,794	23.0	7.2	15.8							
Alabama	470,932	136,220	46,280	89,940	28.9	9.8	19.1							
Louisiana	426,880	125,130	42,983	82,147	29.3	10.1	19.2							
Kentucky	418 922	115 895	39.612	76 283	27.7	9.5	18.2							
Minnesota	487 274	114 774	36 478	78 296	23.6	7.5	16.1							
Washington	492 373	111 303	34 826	76 477	22.6	7.0	15.5							
Oklahoma	383 233	107 760	37 049	70 711	28.1	9.7	18.5							
Maryland	439.074	103 331	31 767	71 564	23.5	7.2	16.3							
South Carolina	339.007	95 562	31 845	63 717	28.2	9.4	18.8							
Connecticut	403 889	92 857	28 771	64 086	23.0	7 1	15.9							
lowa	387 728	91 976	29 141	62 835	23.7	7.5	16.2							
Arkansas	321 450	90.470	31 139	59 331	28.1	9.7	18.5							
Mississinni	299.024	89 953	31 064	58 889	30.1	10.4	19.7							
Arizona	379 578	82 697	25 501	57 196	21.8	67	15.1							
Oregon	341 834	77,330	24 273	53,057	22.6	7 1	15.5							
Kansas	302 189	72 273	22,868	49 405	22.0	7.1	16.3							
West Virginia	240 253	65 472	22,000	43 155	27.3	93	18.0							
Colorado	276 104	63 173	19 751	43,100	22.9	7.2	15.7							
Nebraska	100,665	47 939	15 201	32 6/8	24.0	7.7	16.4							
Maine	150,000	41,000	1/ 201	27 101	27.6	9.5	18.1							
New Mexico	135 274	36 127	12 405	23 722	26.7	9.2	17.5							
Rhode Island	135,274	31 //3	9 707	21,722	20.7	7.2	16.1							
Idaho	106 134	27 933	9.6/1	18 202	26.3	9.1	17.2							
litah	123 388	27,355	8 577	18 918	20.3	7.0	15.3							
Намаіі	104 726	27,435	8 674	18 332	25.8	83	17.5							
Now	104,720	27,000	0,074	10,002	25.0	0.5	17.5							
Hampshire	114,532	26,237	8,155	18,082	22.9	7.1	15.8							
South Dakota	93,402	26,148	9,186	16,962	28.0	9.8	18.2							
District of Co	71,493	23,805	8,134	15,671	33.3	11.4	21.9							
North Dakota	82,782	22,777	7,993	14,784	27.5	9.7	17.9							
Montana	92,485	20,813	6,567	14,246	22.5	7.1	15.4							
Nevada	94,468	19,249	5,845	13,404	20.4	6.2	14.2							
Delaware	69,335	15,969	4,920	11,049	23.0	7.1	15.9							
Vermont	61,306	14,244	4,470	9,774	23.2	7.3	15.9							
Wyomina	39,492	8,928	2,814	6,114	226	7.1	15.5							
Alaska	17.124	3.676	1.138	2.538	21.5	6.6	14.8							

Tregression-Adjusted Synthetic Estimates State Percent Dependent Percent Dependent Los Angeles, CA 770,182 184,822 57,601 127,221 24.0 7.5 Cook, IL 566,715 135,009 41,486 93,523 23.8 7.3 16.5 Cook, IL 231,893 66,997 23,245 43,752 28.9 10.0 18.9 Queens, NY 255,293 61,893 19.097 42,596 24.4 7.5 16.7 Cuyanoga, OH 203,551 47,719 14,604 33,115 23.4 7.2 16.8 Maricoga, AZ 213,577 46,918 11,421 23,249 2.0 6.8 15.2 Harris, TX 164,488 38,936 11.922 27,014 23.7 7.2 16.4 Balt, Civ, MD 100,376 31,189 10,547 23,082 20.1 15.7 14.4 Balt, Civ, MD 100,376 23,178 8,766 16,960 30.2 10.3	TABLE 10: 1986 Dependent Noninstitutionalized Elderly Population by County:							
State Perturbations Total ADL IADL Total ADL IADL Los Angeles, CA 770,182 184,822 57,601 127,221 24.0 7.5 16.5 Philadelphia, PA 240,807 71,559 24,182 47,377 29.7 10.0 19.7 Dade, FL 231,893 66,6997 23,245 43,752 28.9 10.0 18.9 Queens, NY 253,293 61,6939 19,097 42,566 24.4 7.5 16.7 Cuyanoga, OH 203,551 47,719 14,604 33,115 23.4 7.2 16.3 Maricopa, AZ 213,577 46,918 14,419 32,492 20.0 6.8 15.2 Harris, TX 164,488 38,936 11.922 27,014 23.7 7.2 16.4 King, WA 140,282 25,716 8,766 16,960 30.2 10.2 19.9 Jefferson, AL 85,278 25,716 8,766 16,960 32.	Eldorly Number Dependent Dependent							
Los Angeles, CA TOULD TOUL TADL TADL <thtadl< th=""> <thtadl< th=""> TADL</thtadl<></thtadl<>	State	Bopulations				Tetel		
Los Angeles, OA F1012 104,022 31,001 121,221 240 7.3 10.3 Philadelphia, PA 240,807 71,559 24,142 47,377 29.7 10.0 19.7 Dade, FL 231,893 66,997 23,245 43,752 28.8 7.3 16.5 Queens, NY 253,293 61,693 19,097 42,596 24.4 7.5 16.7 Cuyahoga, OH 203,551 47,719 14,604 33,115 23.4 7.2 16.4 Maricopa, AZ 213,577 46,918 14,419 32,499 22.0 6.8 15.2 Harris, TX 164,488 38,936 11,922 27,014 23.7 7.2 16.4 King, WA 148,252 34,343 10,715 23,622 20.1 5.7 14.4 Balt, City, MD 103,576 31,189 10,547 20,642 30.1 10.2 19.9 Jefferson, AL 85,278 25,701 8,071 17.53 1		770 192	19/ 922	57 601	107 001	24.0	ADL 7.5	16.5
Joba, R. Job, T.J. Job. Job. J. J. Job. Job	Lus Angeles, CA	566 715	125.000	41 496	02 522	24.0	7.3	16.5
Primeubpina, PK 240,007 Prima 241,022 Pri, PT 257 10.3 157 Dade, FL 231,893 66,997 23,245 43,752 28,9 10.0 18.9 Queens, NY 253,293 61,693 19,097 42,596 24.4 7.5 16.7 Cuyahoga, OH 203,551 47,719 14,604 33,115 23.4 7.2 16.3 Maricopa, AZ 213,577 46,918 14,419 32,499 22.0 6.8 15.2 Harris, TX 164,488 38,936 11,922 27.014 23.7 7.2 16.4 King, WA 148,252 34,343 10,715 23,062 20.1 5.7 14.4 Batt.City, MD 103,576 31,189 10,547 20,642 30.1 10.2 19.9 Jefferson, AL 85,278 25,710 8,071 17,630 24.1 7.6 16.6 New Haven, CT 106,378 24,500 7.607 16.980 30.4	Dhiladalahia DA	240.907	71 550	2/ 192	93,323	23.0	10.0	10.5
Dade, I.L. Date	Dodo El	240,007	66 007	24,102	47,377	29.7	10.0	19.7
Aubens, INI 247,654 59,915 18,469 41,446 24.2 7.5 16.7 Cuyahoga, OH 203,551 47,719 14,604 33,115 23.4 7.2 16.3 Maricopa, AZ 213,577 46,918 14,419 32,499 22.0 6.8 15.2 Harris, TX 164,488 38,936 11,922 27,014 23.7 7.2 16.4 King, WA 148,252 34,343 10,715 23,628 23.2 7.2 15.9 Middlesex, MA 160,087 32,144 9,062 23,062 20.1 5.7 14.4 Balt, City, MD 103,576 31,189 10,547 20,642 30.1 10.2 19.9 Hennepin, MN 106,475 25,710 8,071 17,630 24.1 7.6 16.6 New Haven, CT 106,378 24,590 7,607 16,983 23.1 7.2 16.0 Milwaukee, WI 122,379 24,335 6,630 15,765 19		253,095	61 602	10.007	43,752	20.9	7.5	16.9
International and the state of the		233,293	50.015	19,097	42,590	24.4	7.5	16.7
Outgrange, AZ 213,577 44,113 14,004 33,110 22.0 6.8 15.2 Harris, TX 164,488 38,936 11,922 27,014 23.7 7.2 16.4 King, WA 144,825 34,343 10,715 23,628 23.2 7.2 15.9 Middlesex, MA 160,087 32,144 9,062 23,082 20.1 5.7 14.4 Balt. City, MD 103,576 31,189 10,547 20,642 30.1 10.2 19.9 Jefferson, AL 85,278 25,716 8,766 16,6693 23.1 7.2 16.0 Miwaukee, WI 122,379 24,335 6,812 17,533 39.9 5.6 14.3 Shelby, TN 78,581 23,878 8,138 15,765 19.4 5.4 44.00 Bergen, NJ 114,975 21,774 6,080 15,694 18.9 5.3 13.6 Ordens, LA 61,464 19,335 6,630 12,705 3.1		247,034	47 710	14,604	41,440	24.2	7.3	16.2
India (D) Partis, TX 164,488 38,936 11,922 27,014 23,7 7.2 16.4 King, WA 148,252 34,343 10,715 23,628 23,2 7.2 16.4 Balt, City, MD 103,576 31,189 10,547 20,642 30,1 10.2 19.9 Jefferson, AL 85,278 25,716 8,766 16,960 30,2 10.3 19.9 Jefferson, AL 85,278 25,716 8,771 17,630 24.1 7.6 16.6 New Haven, CT 106,378 24,590 7,607 16,983 23.1 7.2 16.0 Milwaukee, WI 122,379 24,335 6,812 17,523 19.9 5.6 14.3 Sheloy, TN 78,581 23,678 8,138 15,740 30.4 10.4 20.0 St. Louis, MO 112,770 21,653 6,080 15,694 18.9 5.3 13.6 Providence, RI 86,172 20,369 6,203 1		203,331	47,719	14,004	33,113	23.4	1.2	10.3
Trains, TA 104,466 36,350 11,922 27,014 25,1 7.2 16,4 King, WA 148,252 34,343 10,715 23,628 23,2 7.2 15,9 Middlesex, MA 160,087 32,144 9,062 23,082 20,1 5,7 14,4 Balt, City, MD 103,576 31,189 10,547 20,642 30,1 10,2 19,9 Jefferson, AL 85,278 25,716 8,756 16,960 30,2 10,3 19,9 Hennepin, MN 106,475 25,701 8,071 17,630 24,1 7,6 16,6 New Haven, CT 106,378 24,335 6,812 17,523 19,9 5,6 14,3 St. Louis, MO 112,770 21,853 6,088 15,766 19,4 5,3 13,6 Providence, RI 86,172 20,369 6,300 14,069 23,6 7,3 16,3 Honolulu, HI 76,008 19,656 6,263 13,333 25,	Harria TV	213,377	29 026	14,419	32,499	22.0	0.0	10.2
Ning, WA 140,222 33,943 107,13 23,023 22,22 1,22 10,23 Middlesex, MA 160,067 32,144 9,062 23,082 20,1 5,7 14,4 Balt. City, MD 103,576 31,189 10,547 20,642 30,1 10,2 19,9 Hennepin, MN 106,475 25,716 8,071 17,630 24,1 7,6 16,6 New Haven, CT 106,378 24,590 7,607 16,983 23,1 7,2 16,0 Milwaukee, WI 122,379 24,335 6,812 17,523 19,9 5,6 14,3 Shelby, TN 78,581 23,878 8,138 15,740 30,4 10,4 20,0 St. Louis, MO 112,770 21,853 6,080 15,664 18,9 5,3 13,6 Honolulu, HI 76,008 19,856 6,263 13,393 25,9 8,2 17,6 Orleans, LA 61,464 19,335 6,630 12,705 31,1	King WA	1/19 252	30,930	10,922	27,014	23.7	7.2	10.4
Inductada, IND 100,007 3,02 21,002 20,11 10.7 11-4- Balt, City, MD 103,576 31,189 10,547 20,642 30.1 10.2 19.9 Hennepin, MN 106,475 25,716 8,756 16,960 30.2 10.3 19.9 Hennepin, MN 106,475 25,716 8,071 17,630 24.1 7.6 16.6 New Haven, CT 106,378 24,590 7,607 16,983 23.1 7.2 16.0 Miwaukee, WI 122,379 24,335 6,812 17,523 19.9 5.6 14.3 Shelby, TN 78,581 23,878 8,138 15,765 19.4 5.4 14.0 Bergen, NJ 114,975 21,774 6,080 15,694 18.9 5.3 13.6 Providence, RI 86,172 20,369 6,300 14,069 23.6 7.3 16.3 Untomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 </td <td>Middlesex MA</td> <td>140,232</td> <td>32 1//</td> <td>0.062</td> <td>23,020</td> <td>20.1</td> <td>5.7</td> <td>11.9</td>	Middlesex MA	140,232	32 1//	0.062	23,020	20.1	5.7	11.9
Jahr. Coty, MD 103,376 25,716 8,757 103,477 25,701 30,17 102,2 10.2 <th10.2< th=""> <th< td=""><td>Balt City MD</td><td>103,576</td><td>31 180</td><td>9,002 10.547</td><td>20,642</td><td>20.1</td><td>10.2</td><td>14.4</td></th<></th10.2<>	Balt City MD	103,576	31 180	9,002 10.547	20,642	20.1	10.2	14.4
Johnson, MN Johnson	Lefferson Al	85 278	25 716	8 756	16 960	30.7	10.2	10.0
Internepin, Min 100,473 23,701 0,071 17,030 24.1 7.0 100. Milwaukee, WI 122,379 24,335 6,812 17,523 19.9 5.6 14.3 Shelby, TN 78,581 23,878 8,138 15,740 30.4 10.4 20.0 St. Louis, MO 112,770 21,853 6,088 15,765 19.4 5.4 14.0 Bergen, NJ 114,975 21,774 6,080 15,694 18.9 5.3 13.6 Honolulu, HI 76,008 19,656 6,630 12,705 31.5 10.8 20.7 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 18.6 Marion, IN 61,372 16,774 4,757 12,017	Hennenin MN	106 475	25,710	8.071	17,630	24.1	7.6	16.6
New Havel, C1 100,373 24,335 6,812 17,523 19.9 5.6 14.3 Shelby, TN 78,581 23,378 8,138 15,740 30.4 10.4 20.0 Shelby, TN 78,581 23,878 8,138 15,765 19.4 5.4 14.0 Shelby, TN 78,581 23,878 6,080 15,694 18.9 5.3 13.6 Providence, RI 86,172 20,369 6,300 14,069 23.6 7.3 16.3 Hultnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 13,017 27.3 <		106,473	24,500	7,607	16,093	24.1	7.0	16.0
Immutative, Wi 122,379 24,335 6,812 17,353 19.9 3.0 14.3 Shelby, TN 78,581 23,878 8,138 15,740 30.4 10.4 20.0 St. Louis, MO 112,770 21,853 6,088 15,740 30.4 10.4 20.0 Bergen, NJ 114,975 21,774 6,080 15,694 18.9 5.3 13.6 Providence, RI 86,172 20,389 6,300 14,069 23.6 7.3 16.3 Honolulu, HI 76,008 19,656 6,263 13,393 25.9 8.2 17.6 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.4 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.5 Oklahoma, OK 65,010 18,351 6,231 12,107 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5	New Haven, CT	100,370	24,090	6,007	17,503	23.1	1.Z	14.2
Shi Euby, IN 76,361 23,878 6,135 10,740 30.4 10.4 20.0 Bergen, NJ 111,975 21,774 6,080 15,765 19.4 5.3 13.6 Providence, RI 86,172 20,369 6,300 14,069 23.6 7.3 16.3 Honolulu, HI 76,008 19,656 6,263 13,393 25.9 8.2 17.6 Orleans, LA 61,464 19,335 6,630 12,705 31.5 10.8 20.7 Multinomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Futon, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,107 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5	Shalby TN	70 501	24,333	0,012	17,525	19.9	5.0	14.3
Sd. Louis, MO 112,170 21,835 6,086 10,765 114,470 144,075 Providence, RI 86,172 20,369 6,080 14,069 23.6 7.3 16.3 Honolulu, HI 76,008 19,656 6,263 13,393 25.9 82 17.6 Orleans, LA 61,464 19,335 6,630 12,705 31.5 10.8 20.7 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,107 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Marion, IN 61,372 16,774 4,757 12,017 22.5 7.0	Stillouin MO	112 770	23,070	6,130	15,740	30.4	10.4 5.4	20.0
Beitgein, NJ 114,975 21,774 6,080 15,894 16.9 5.3 13.8 Providence, RI 86,172 20,369 6,300 14,069 23.6 7.3 16.3 Orleans, LA 61,464 19,335 6,630 12,705 31.5 10.8 20.7 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Futton, GA 60.972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Clark, NV 54,643 10,037 3,083 6,954 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 <td< td=""><td>St. LOUIS, IVIO</td><td>112,770</td><td>21,000</td><td>6,080</td><td>15,765</td><td>19.4</td><td>5.4</td><td>14.0</td></td<>	St. LOUIS, IVIO	112,770	21,000	6,080	15,765	19.4	5.4	14.0
Prioriderice, Ri 86, 172 20,369 6,300 14,065 23.6 7.7.3 16.3 Honolulu, HI 76,008 19,866 6,263 13,393 25.9 82 17.6 Orleans, LA 61,464 19,335 6,630 12,705 31.5 10.8 20.7 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7.696	Dergen, NJ Drovidence, DI	114,975	21,774	6,060	15,694	10.9	5.3	13.0
Individui, Ini 76,005 19,056 6,263 13,393 23.9 6.2 17.6 Orleans, LA 61,464 19,335 6,630 12,705 31.5 10.8 20.7 Multnomah, OR 79,847 19,274 6,069 13,205 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2	Honolulu III	76,009	20,369	6,300	14,069	23.0	7.3	10.3
Olitearis, LA 61,464 19,353 6,630 12,705 31.5 10.5 20.7 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.6 16.5 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,641 6,967 24.0 7.		76,008	19,000	6,203	13,393	25.9	0Z	17.0
Midmonian, Ork 19,847 19,274 6,069 13,203 24.1 7.6 16.3 Jefferson, KY 79,520 19,164 5,889 13,275 24.1 7.4 16.7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 <t< td=""><td>Multaomah OP</td><td>01,404</td><td>19,335</td><td>6,030</td><td>12,705</td><td>31.5</td><td>10.0</td><td>20.7</td></t<>	Multaomah OP	01,404	19,335	6,030	12,705	31.5	10.0	20.7
Jenerson, K1 73,020 19,164 5,069 13,273 24,1 7,4 16,7 Fulton, GA 60,972 18,991 6,416 12,575 31.1 10.5 20.6 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,659 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,309 22.2 6.8 </td <td>Induction Indian, OK</td> <td>79,047</td> <td>19,274</td> <td>5,009</td> <td>13,205</td> <td>24.1</td> <td>7.0</td> <td>10.0</td>	Induction Indian, OK	79,047	19,274	5,009	13,205	24.1	7.0	10.0
Pullon, GA 60,972 16,991 6,416 12,573 31.1 10.3 20.8 Oklahoma, OK 65,010 18,351 6,231 12,120 28.2 9.6 18.6 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 <td>Jellerson, Kr</td> <td>79,520</td> <td>19,104</td> <td>5,009</td> <td>13,275</td> <td>24.1</td> <td>1.4</td> <td>10.7</td>	Jellerson, Kr	79,520	19,104	5,009	13,275	24.1	1.4	10.7
Orkatolina, OK 65,010 16,331 12,120 26.2 9.0 16.8 Marion, IN 61,372 16,774 4,757 12,017 27.3 7.8 19.6 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3<	Chiphomo OK	65.010	10,991	6 224	12,575	31.1	10.5	20.0
Mathur, IN 61,312 10,174 4,137 12,017 27.3 7.8 19.0 Denver, CO 62,887 15,395 4,838 10,557 24.5 7.7 16.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 <td>Marian IN</td> <td>61 272</td> <td>16,301</td> <td>0,231</td> <td>12,120</td> <td>20.2</td> <td>9.0</td> <td>10.0</td>	Marian IN	61 272	16,301	0,231	12,120	20.2	9.0	10.0
Deriver, CO 02,037 13,33 4,035 10,037 24,3 1.7. 10.8 Salt Lake, UT 51,619 11,630 3,613 8,017 22.5 7.0 15.5 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8<	Donvor CO	62.997	15 205	4,757	12,017	27.5	7.0	19.0
Stat Lake, OT St,013 H,050 S,017 Z2.5 F.0 H.3 Clark, NV 54,643 11,017 3,321 7,696 20.2 6.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2	Salt Jake LIT	51 610	11 630	4,030	8 017	24.5	7.0	15.5
Original Pulaski, AR 35,744 10,363 3,521 7,030 20.2 0.1 14.1 Pulaski, AR 35,744 10,363 3,520 6,843 29.0 9.8 19.1 New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.	Clark NV	54 643	11,030	3 3 2 1	7,696	22.5	6.1	14.1
New Castle, DE 43,351 10,037 3,083 6,954 23.2 7.1 16.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 </td <td>Pulaski AR</td> <td>35 744</td> <td>10.363</td> <td>3 520</td> <td>6.843</td> <td>20.2</td> <td>0.1</td> <td>19.1</td>	Pulaski AR	35 744	10.363	3 520	6.843	20.2	0.1	19.1
New Odstie, DL 40,001 10,007 0,003 0,004 23.2 1.1 10.0 Mecklenburg, NC 41,666 10,008 3,041 6,967 24.0 7.3 16.7 Douglas, NE 41,539 9,993 3,109 6,884 24.1 7.5 16.6 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,925 2,121 4,804 22.8 7.0 </td <td>New Castle DE</td> <td>/3 351</td> <td>10,000</td> <td>3.083</td> <td>6 95/</td> <td>23.0</td> <td>7.1</td> <td>16.0</td>	New Castle DE	/3 351	10,000	3.083	6 95/	23.0	7.1	16.0
Incord Hourg, No41,50010,0003,0410,50724.07.516.7Douglas, NE41,5399,9933,1096,88424.17.516.6Greenville, SC34,6339,4903,1446,34627.49.118.3Sedgwick, KS40,0889,2502,8486,40223.17.116.0Bernalillo, NM41,1249,1092,8006,30922.26.815.3Hinds, MS26,5938,1502,7875,36330.610.520.2Polk, IA33,5807,9642,4645,50023.77.316.4Hillsborough, NH31,8817,3362,2595,07723.07.115.9Cumberland, ME29,5576,9542,1714,78323.57.316.2Kanawha, WV30,4126,9252,1214,80422.87.015.8Ada, OD18,1904,0591,2612,79822.36.915.4Minnehaha, SD12,8093,0079472,06023.57.416.1Henrico, VA12,6212,8139491,96522.36.715.6Yellowstone, MT11,4242,5527941,75822.37.015.4Chittenden, VT9,6852,2767041,57223.57.316.2Laramie, WY5,6671,30341189223.07.315.7Anchorage, AK5,7861,	Mecklenburg NC	41,666	10,007	3,000	6 967	24.0	7.1	16.7
Bodglas, NL 41,355 3,355 3,165 0,064 24.1 1.3 16.0 Greenville, SC 34,633 9,490 3,144 6,346 27.4 9.1 18.3 Sedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.7 <	Douglas NE	41,530	0 003	3 109	6,884	24.0	7.5	16.6
Stedgwick, KS 40,088 9,250 2,848 6,402 23.1 7.1 16.0 Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hildsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 <	Greenville SC	34 633	9,995	3,103	6346	27.1	9.1	18.3
Bernalillo, NM 41,124 9,109 2,800 6,309 22.2 6.8 15.3 Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 1	Sedawick KS	40.088	9,450	2 8/8	6,02	27.4	7.1	16.0
Hinds, MS 26,593 8,150 2,787 5,363 30.6 10.5 20.2 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2	Bernalillo NM	41 124	9 109	2,040	6 309	20.1	6.8	15.3
Initial, Mo 20,000 0,100 2,101 0,000 000 20,000 20,202 Polk, IA 33,580 7,964 2,464 5,500 23.7 7.3 16.4 Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 <td< td=""><td>Hinds MS</td><td>26 593</td><td>8 150</td><td>2,000</td><td>5 363</td><td>30.6</td><td>10.5</td><td>20.2</td></td<>	Hinds MS	26 593	8 150	2,000	5 363	30.6	10.5	20.2
Hillsborough, NH 31,881 7,336 2,259 5,077 23.0 7.1 15.9 Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Polk IA	33,580	7 964	2 464	5,500	23.7	7.3	16.4
Cumberland, ME 29,557 6,954 2,171 4,783 23.5 7.3 16.2 Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Hillsborough, NH	31,881	7,336	2,259	5.077	23.0	7.1	15.9
Kanawha, WV 30,412 6,925 2,121 4,804 22.8 7.0 15.8 Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Cumberland MF	29.557	6.954	2 171	4 783	23.5	7.3	16.2
Ada, OD 18,190 4,059 1,261 2,798 22.3 6.9 15.4 Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Kanawha WV	30 412	6.925	2 121	4 804	22.8	7.0	15.8
Minnehaha, SD 12,809 3,007 947 2,060 23.5 7.4 16.1 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Ada OD	18 190	4 059	1 261	2 798	22.3	6.9	15.4
Hamiltoniana, OD 12,000 0,001 0 H 2,000 101 101 Henrico, VA 12,621 2,813 949 1,965 22.3 6.7 15.6 Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Minnehaha SD	12 809	3 007	947	2,060	23.5	74	16.1
Yellowstone, MT 11,424 2,552 794 1,758 22.3 7.0 15.4 Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Henrico VA	12 621	2 813	949	1,965	22.3	67	15.6
Chittenden, VT 9,685 2,276 704 1,572 23.5 7.3 16.2 Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Yellowstone MT	11 424	2,513	794	1,303	22.0	7.0	15.0
Cass, ND 8,645 2,056 655 1,401 23.8 7.6 16.2 Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Chittenden VT	9 685	2 276	704	1,700	23.5	7.3	16.2
Laramie, WY 5,667 1,303 411 892 23.0 7.3 15.7 Anchorage, AK 5,786 1,168 346 822 20.2 6.0 14.2	Cass ND	8 645	2,2,0	655	1 401	23.8	7.6	16.2
Anchorage AK 5.786 1.168 346 822 20.2 6.0 14.2	Laramie WY	5 667	1 303	411	892	23.0	7.3	15.7
	Anchorage, AK	5,786	1,168	346	822	20.2	6.0	14.2

APPENDIX A

The log-linear model used in the analysis produces two sets of parameter estimates: one for the logged ratio of not dependent to ADL dependent, and one for the logged ratio of IADL dependent to ADL dependent. These equations produced from our analysis can be written as:

 $log (P_1/P_3) = 2.51 - 0.178 - 0.41R - 0.59A - 0.11A^2 - 0.35P$ $log (P_2/P_3) = 0.44 + 0.718 - 0.02R - 0.20A - 0.07A^2 - 0.15P$

where

- P_2 = the probability of being independent;
- P_2 = the probability of being IADL dependent;
- P_3 = the probability of being ADL dependent;
- S = sex (coded 1 if female and 0 if male);
- R = race (coded 1 if nonwhite and 0 if white);
- A = age group (coded -2 if 65-69, -1 if 7074, 0 if 75-79, 1 if 80-84, and 2 if 85 or over);
- A^2 = the square of the variable "A"; and
- P = the percent of elderly in poverty (coded -1 if <8%, 0 if between 8-15% and 1 if >15%).

For ease of illustration, let

 $E1 = \log (P_1/P_3)$ and $E2 = \log (P_2/P_3)$.

Taking the exponent of both sides of both equations yields

$$e^{E1} = P_1/P_3$$
 and $e^{E2} = P_2/P_3$

As, by definition $P_1+P_2+P_3 = 1$, the three equations can be solved simultaneously for P_1 , P_2 and P_3 . The result is:

APPENDIX B

Logistic Regression Results: Rate of Nursing Home Institutionalization							
Variable	Coefficient	Standard Error	Chi-Square	d.f.	p-value		
Female ¹	0.50	0.09	30.08	1	0.001		
Age Group ²	0.85	0.04	580.17	1	0.001		
Age Group-Square ³	0.07	0.03	7.62	1	0.006		
North Central ⁴	0.31	0.09	12.56	1	0.001		
Intercept	-3.67	0.10	1425.73	1	0.001		
Model chi-square = 1013.17, df = 4, p<0.001							
1. Coded 1 if female and 0 if male							
2. Coded -2 if 65-69, -1 if 70-74, 0 if 75-79, 1 if 80-85 and 2 if 85 or over							
3. Coded as the square of the age group variable, i.e. 4, 2, 0, 2 or 4							
4. Coded 1 if north central and 0 otherwise							

SOFTWARE TO PRODUCE SMALL AREA REGRESSION-ADJUSTED SYNTHETIC ESTIMATES OF FUNCTIONAL DEPENDENCY AMONG THE ELDERLY

Prepared by Jane D. Darter¹ Jennifer M. Elston² William G. Weissert³

of the Program on Aging School of Public Health The University of North Carolina at Chapel Hill

Under ASPE Grant No. 87ASPE181A, Assistant Secretary for Planning and Evaluation United States Department of Health and Human Services Floyd Brown, Project Office

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SMALL AREA REGRESSION-ADJUSTED SYNTHETIC ESTIMATES OF FUNCTIONAL DEPENDENCY

Produced by

Program on Aging School of Public Health The University of North Carolina

Under ASPE Grant No. 87ASPE181A

Press any key to continue ...

INTRO 1 OF 6

OldEst is designed for use in planning long-term care services for the elderly in your community.

OldEst estimates the noninstitutionalized elderly population in your community who are functionally dependent. OldEst provides ranges of estimates based on the age, sex, race, and the percentage of the community's elderly population that resides in poverty.

Press any key to continue ...

INTRO 2 OF 6

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Press <u>I</u> for future information, or any other key to go to MAINMENU:

INTRO 3 OF 6

OldEst estimates two levels of functional dependency:

Activities of Daily Living (ADL):

ADL dependent individuals report difficulty with and receive human assistance with eating, transferring, toileting, dressing, or bathing.

Mobility/Instrumental Activities of Daily Living (IADL):

IADL dependent individuals report difficulty with and receive human assistance with inside and outside mobility, meal preparation, grocery shopping, money management, light and heavy housework, or using the telephone.

Summing the ADL and IADL estimates yields estimates of the total dependent population. In addition to ADL, IADL and total dependent population point estimates, OldEst will also produce expected ranges for each of these estimates.

Press <u>I</u> for future information, or any other key to go to MAINMENU:

INTRO 4 OF 6
OldEst computes estimates using a statistical formula developed from national data reported in 1984. (Detailed information about OldEst calculations is included in your OldEst manual.)
OldEst makes estimates based upon two assumptions. First, that age, sex, race, and poverty- specific disability rates have not changed between 1984 and the year of your community data. Second, that the relationship between dependency and age, sex, race, and the percent of the elderly residing in poverty is the same as national averages. Thus, the estimates will err to the extent that the relationship between dependency and age, sex, race, and poverty in your community have changed over time, and to the extent that the relationships vary from the national averages.
Press <u>I</u> for future information, or any other key to go to MAINMENU:

INTRO 5	5 OF 6						
To pi follov	roduce deper wing informati	ndency estimate	es for the eld	lerly in your	community,	you will be	e asked to enter the
(COMMUNITY	′ NAME:			YEAR:		
	NONINSTI	TUTIONALIZEI	O or TOTAL	ELDERLY F	POP. BY RA	CE, SEX, A	AND AGE
l l	RACE White	SEX Male Fomalo	65-69	70-74	75-79	80-84	85 & Over
1	Nonwhite	Male Female					
I	Percent of the	e community's e	elderly popul	ation residir	ng in poverty	/	
Press <u>I</u>	for future info	ormation, or any	/ other key to	o go to MAII	NMENU:		



1	2	3	4
INTRO	ENTRY	DISPLAY/PRINT	EXIT
	=====		@
~~~~~~	=====		
Introduction,	Enter population	View ADL and IADL	Exit
and	by race, sex & age	estimates on screen,	program
description	or use stored data	or print summaries	

### ENTRY MENU

- 1 .. Enter new community data
- 2.. Retrieve existing data
- 3 .. Edit current data
- 4 .. Return to MAINMENU

Please enter the number corresponding to your choice: _____

				, , , , , , , , , , , , , , , , , , , ,		
COMMUNIT	Y NAME:			YEAR:		
Are these N	ONINSTITUTI	ONALIZED o	r TOTAL po	pulation num	nbers? (N/T	):
RACE White	SEX Male	65-69	70-74	75-79	80-84	85 & Ovei
	Female					
Nonwhite	Male					
	Female					
Percent of elderly po	pulation resid	ing in poverty				
Use the $\uparrow \downarrow \rightarrow \leftarrow$ keys	s to move curs	or around scr	reen.			
Do you wish to save	this data perm	nanently? (Y/	N)			
Press any key to col	nunue					

Select already existing community data						
COMMUNITY NAME	YEAR	PERCENT POVERTY				
Please enter the number corresponding to your choice	:					

DISPLAY/PRINT MENU	
COMMUNITY:	
<ol> <li>DISPLAY Population Summary</li> <li>DISPLAY ADL Estimates</li> <li>DISPLAY IADL Estimates</li> <li>DISPLAY TOTAL Estimates</li> </ol>	
A PRINT Population Summary B PRINT ADL Estimates C PRINT IADL Estimates D PRINT TOTAL Estimates E RETURN TO MAINMENU	
	-
Please enter the number or letter corresponding to your choice:	

ADL DEPENDENT POINT ESTIMATES								
	For _							
RACE White	SEX Male Female Both	65-69 	70-74	75-79	80-84	85 & Over		
Nonwhite	Male Female Both							
All Races	Male Female Both							
Press any key to continue								

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