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A State-Based Regression Model for Estimating Substate Life Expectancy

David A. Swanson
Department of Sociology, Pacific Lutheran University, Tacoma, Washington 98447

Life expectancy is an important indicator of the level of mortality in a population. However, the conventional way of calculating life expectancy—constructing a life table—has rigorous data requirements. As a consequence, life expectancy data are not usually available for substate areas. In this article, a regression model for estimating life expectancy is constructed, using state-level data, and is tested against two sets of 1980 life expectancy data: (1) a nationwide sample of metropolitan areas and (2) selected cities, their suburbs, and rural counties in Ohio. An additional test shows the sensitivity of the model's accuracy to errors in one of its input data elements. The results suggest that the model should be given serious consideration for generating life expectancy estimates for substate areas.

Life expectancy is an important indicator of the level of mortality experienced by a population. Its principal advantage over other methods of measuring mortality is that it does not reflect the effects of the age distribution of an actual population and does not require the adoption of a standard population for comparing levels of mortality among different populations. The usual way to obtain life expectancy, however, is through the construction of a life table, which has rigorous data requirements and often entails a great deal of personnel time.

As a consequence of these data and time demands, life expectancy information is not often available for substate areas. This is unfortunate because Swanson and Stockwell (1986) found that there are substate area effects on life expectancy in Ohio and, further, that these effects exist for both the black and white populations (Swanson and Stockwell, 1988). These findings indicate that national- and state-level life expectancy values are not uniformly applicable to small area populations and that there may be unsuspected life expectancy differentials across various substate areas. It is also unfortunate because life expectancy represents an important potential indicator for health planning, which is generally accomplished at substate levels [Feinlieb, 1984; National Center for Health Statistics (NCHS), 1984; Wennberg and Gittelsohn, 1975, 1980] without benefit of life expectancy information. [An exception to this is the state of Indiana (1983), which generates life expectancy information for its health service areas and subareas for purposes of planning.]

In theory, there are four general methodologies that could be used to estimate life expectancy for substate populations in the United States. The first is based on stable population concepts (Carrier and Hobcraft, 1971; Coale, 1984; Coale and Demeny, 1966; Horiuchi and Coale, 1982; Mitra, 1984; Preston and Hill, 1980). The second is based on biological theories of aging (Burch, 1967; Siler, 1979). The third is based on the estimation of population by age (Bousfield, 1977; Irwin, 1980, 1984, 1985; Martin and Serow, 1978). The fourth type uses regression equations that exploit the relationship between life expectancy and certain other demographic indices. This approach was developed by Mazur (1969a,b, 1971, 1972) and tested and refined by Swanson and Palmore (1976), Swanson, Palmore, and Sundarum (1977), and Gunasekaran, Palmore, and Gardner (1981).

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The methodology based on stable population concepts is inherently unsuited for substate areas because it requires the assumption of not only stable mortality and fertility rates but also no migration—yet migration is the most influential source of variation in population change among small areas (Lee and Goldsmith, 1982; National Research Council, 1980). The second type is also not well-suited for substate areas because, among other reasons, biological theories of aging have rigorous data requirements that cannot be met with the data usually available for small areas (Siler, 1979). The third type is more suitable; however, the only *single* source of substate population data by age is the U.S. Bureau of the Census, which provides enumerations of their populations by age only once every 10 years and *postcensal estimates* that suffer from high levels of inaccuracy for certain age groups (Irwin, 1985) and, moreover, are not available for a minimum of 2 years after the estimate data (Irwin, 1985). Regression estimation, then, represents the most promising approach for developing accurate, cost-effective, and timely estimates of life expectancy for substate populations in countries like the United States.

The regression-based method is well-suited for estimating life expectancy for substate areas for the following reasons:

1. No assumptions of stability or quasi-stability are required (Swanson and Palmore, 1976:5).
2. The data requirements can be met by obtaining only three elements that are available in the U.S. on an annual basis (Swanson, 1977): (a) total deaths, (b) total population (estimated or enumerated), and (c) the population aged 65 years and over (estimated or enumerated).
3. It has been found to be accurate for large area populations (Gunasekaran, Palmore, and Gardner, 1981; Swanson and Palmore, 1976; Swanson, Palmore, and Sundarum, 1977).
4. Although its accuracy for substate areas has been tested less extensively than for large areas, results to date indicate that it can produce accurate estimates of life expectancy (Swanson and Stockwell, 1986; Swanson and Swanson, 1978).
5. Annual postcensal estimates of life expectancy can be produced in a timely manner (Swanson, 1977).

The State-Based Model for Estimating Life Expectancy

The technique used to estimate life expectancy requires only two data elements: the crude death rate and the percentage of the population aged 65 years and over. The regression model underlying the life expectancy estimates presented in the following section was constructed by using state-level data for 1980. Table 1 provides the characteristics of the regression model constructed using 1980 data for the 50 states and the District of Columbia.[1] This model is more streamlined than earlier ones developed by Mazur (1969a, 1972) and Swanson and Palmore (1976) because it does not depend on two separate regression equations that are later combined into a single estimation equation. Further, the model was the result of some experimentation with different functional forms that revealed that the best fitting regression, while still using only two data elements, resulted from a full quadratic model.

The equation given in Table 1 provides accurate estimates of life expectancy at birth because the percentage of the population aged 65 years and over increases exponentially as a function of relative mortality (Swanson, Palmore, and Sundarum, 1977). Further, as mathematically proven by Swanson, Palmore, and Sundarum (1977), the index used to measure relative mortality, which is implicitly found in the equation, is itself an index of population aging. Given this index and its exponential relationship with the percentage of the population aged 65 years and over, the relationship of P65+ with life expectancy at birth is approximately logarithmic.[2]

Table 1. Characteristics of the Regression Model for Estimating Life Expectancy at Birth

Variable	Regression coefficient
CDR	−4.2443
ln(P65+)	3.0160
CDR^2	0.0267
$[\ln(P65+)]^2$	0.1773
[ln(P65+)](CDR)	0.8707
(Constant)	82.2761
R^2 = 0.7401	
S.E.E. = 0.7371	
N = 51	

Note: CDR = (Deaths/Population) × 1000. ln(P65+) = natural logarithm of the percentage of the population aged 65 years and over: ln[(population 65+/total population) × 100].

Source: The population data underlying this model were obtained from U.S. Bureau of the Census (1983a:Table 67). The mortality data are from National Center for Health Statistics (1985b:Tables 1–12). The life expectancy data are from National Center for Health Statistics (1985c:2–3).

Test of Accuracy for Metropolitan Statistical Areas, 1980

For a test of the regression model given in Table 1, 30 metropolitan statistical areas (MSAs) were selected from the 305 for which deaths were reported by age in 1980 (NCHS, 1985a) by using a random start and a systematic 1-in-10 selection. Appropriate age data for these 30 MSAs were then obtained from 1980 census data (U.S. Bureau of the Census, 1983b). The Greville method of abridged life table construction (Shryock, Siegel, and Assocs., 1976:225–256) was used to obtain life expectancy at birth for each MSA.

The regression model, along with the required data elements (the crude death rate and the percentage of the population aged 65 years and over), was used to generate 1980 life expectancy estimates for the 30 MSAs. Table 2 gives these estimates along with the actual life expectancy figures calculated by the construction of life tables. The summary indices of error in Table 2 show that the overall accuracy of the model is quite high: the mean error is 0.26 year and the mean absolute error is 0.77 year. Further, only three of the 30 MSAs have an absolute error in excess of 1.0 year and the maximum error found, 4.68 years, is for the Fort Lauderdale–Hollywood, Florida, MSA. There appears, however, to be some bias in the estimates, with slightly more than half (57 percent) of the areas being underestimated.

As a formal means of evaluating this underestimation bias, a one-tailed t test for paired observations was conducted to determine whether the estimated values were significantly lower than the actual life expectancy values. At $\alpha = 0.05$, the test showed that the estimated values are not significantly lower [$T = 1.11$, df = 29, and $\Pr(T = 1.11) > 0.05$].

One noticeable feature of the actual MSA life expectancy values presented in Table 2 is the low amount of variation (standard deviation = 1.78 years). Given this, it is reasonable to ask whether the *mean* 1980 life expectancy for all 51 states is a plausible alternative to the regression-based estimator. Using these data, this mean life expectancy is 73.98 years.

Applying this value to each of the 30 MSAs shown in Table 2, the following is found: 14 MSAs are underestimated and 16 are overestimated; the mean error is 0.27 year; the mean absolute error is 1.31 years; and in 16 MSAs the absolute estimation error is greater than 1 year. Two of these criteria for evaluating accuracy indicate that the mean value as an estimator is at least as suitable as that generated by the regression model: its mean error is only 0.27 and only 14 out of 30 are underestimated. However, the remaining two accuracy criteria are important: (1) The mean generated 16 (out of 30) extreme errors, whereas the regression model generates only 3 (out of 30) extreme errors; and (2) the mean absolute error of the regression estimates is only 60 percent of the mean absolute error found by using the mean estimator. Since the amount of variation in MSA life expectancy is relatively small, it would seem especially important to reduce the probability of having an extreme error. This implies

Table 2. Estimated and Actual 1980 Life Expectancy by Selected MSA

MSA	Life expectancy at birth		
	Estimated	Actual	Error
Albuquerque, NM	74.73	73.99	0.74
Appleton-Oshkosh, WI	75.38	75.72	−0.34
Baton Rouge, LA	73.36	72.66	0.70
Bismark, ND	75.88	71.97	3.91
Buffalo, NY	72.80	73.28	−0.48
Charlottesville, VA	73.69	73.20	0.49
Columbus, GA–AL	71.92	70.98	0.94
Denver–Boulder, CO	75.06	75.31	−0.25
Erie, PA	72.56	72.28	0.28
Fort Lauderdale–Hollywood, FL	78.62	73.94	4.68
Glens Falls, NY	73.18	73.47	−0.29
Harrisburg, PA	72.95	73.32	−0.37
Jackson, MI	72.79	72.06	0.73
Kansas City, MO–KS	73.05	73.19	−0.14
Lancaster, PA	73.92	74.57	−0.65
Lincoln, NB	76.04	76.70	−0.66
Madison, WI	76.11	76.43	−0.32
Minneapolis–St. Paul, MN	75.26	75.88	−0.62
New Brunswick–Perth Amboy–Sayreville, NJ	73.56	73.89	−0.33
Northeast PA	73.86	72.95	0.91
Parkersburg–Marietta, WV, OH	73.46	74.05	−0.59
Pittsfield, MA	66.26	68.04	−1.78
Reading, PA	74.42	74.18	0.24
Rock Hill, SC	72.49	71.63	0.86
San Angelo, TX	74.72	74.01	0.71
Seattle–Everett, WA	74.86	75.34	−0.48
Springfield, MO	75.41	75.49	−0.08
Terre Haute, IN	73.04	73.12	−0.08
Vallejo–Fairfield–Napa, CA	75.23	75.04	0.19
Wichita, KS	74.47	74.70	−0.25

Note: Mean error = 0.26; mean absolute error = 0.77; number overestimated = 13; number underestimated = 17; number of absolute errors in excess of 1.0 year = 3.

that the regression model should be preferred over the "mean" state life expectancy values as an estimator.

To determine whether the absolute errors resulting from the use of the regression equation were significantly lower than those resulting from the use of the 51-state mean as an estimator, the one-tailed t test for paired observations was again used. At $\alpha = 0.05$, the absolute errors resulting from the regression equation were significantly lower than those resulting from using the mean as an estimator [$T = 1.99$, df = 29, and $\Pr(T = 1.99) < 0.05$].

Further inspection of Table 2 reveals that there may be some regional bias in the model because life expectancy in each of the 7 MSAs in the South is overestimated. This suggests that, at least for the South, one might expect consistent overestimation of MSA life expectancy.

Test of Accuracy for Substate Areas in Ohio, 1980

To provide an idea of the suitability of the regression model in estimating life expectancy for a wider range of substate areas, its accuracy was tested for Ohio's major cities, their corresponding suburban areas, and the state's rural counties.[3] The 1980 age data used to construct life tables for these areas were obtained from published reports (U.S. Bureau of the Census, 1983b); the 1980 death data were obtained from a computer tape provided by the Ohio Office of Vital Statistics.[4] Actual life expectancy values were obtained, again, by using Greville's method.

The estimated and actual life expectancy figures are presented in Table 3 along with summary indices of accuracy. In terms of mean error and mean absolute error, the estimates for substate areas in Ohio are more accurate than those for MSAs. There is a very strong tendency, however, toward underestimation (23 out of 36 areas), although the proportion of areas with extreme errors (in excess of 1.0 year) is less than that found for the MSAs. This tendency is especially apparent among the seven suburban areas, which are all underestimated. The opposite tendency is found for the cities: five out of seven are overestimated. The least biased subset is the rural counties, where only 14 out of 22 are underestimated.

As was done earlier with the MSA data, the mean 1980 life expectancy for all 51 states (73.98) was considered as a possible alternative estimator to the regression model. Using this estimator, the mean error was found to be 0.20, the mean absolute error was 1.37, the number of absolute errors in excess of 1.0 year was 19 (out of 36), and 53 percent were underestimated. A comparison between these indices of accuracy of the regression-based estimator and the mean estimator shows that the regression estimator has a much lower mean absolute error and far fewer extreme errors; the mean estimator, however, is less biased in terms of underestimation.

A one-tailed t test for paired observations showed that the absolute errors resulting from the regression equation were significantly lower than those associated with the mean estimator [$T = 4.61$, df = 35, and $\Pr(T = 4.61) < 0.05$].

Accuracy Test Using Estimates of the Population Aged 65 and Over

One potential use of the model is to estimate life expectancy for noncensus years. In this regard, the model is best suited for use with individual counties or aggregates of counties because estimated figures for the total population and the population aged 65 years and over (P65+) are routinely generated for counties by the Bureau of the Census and various state demographic centers. Estimates of P65+ for counties are also provided by the U.S. Administration on Aging. Since the second of these two data items is subject to the largest relative estimation error, the accuracy of the model for the 30 MSAs selected earlier was examined by using estimated P65+ values for 1980.

Table 3. Estimated and Actual 1980 Life Expectancy for Selected Cities and Their Suburbs and Rural Counties in Ohio

Area	Life expectancy at birth		
	Estimated	Actual	Error
City			
Akron	72.72	72.54	0.18
Cincinnati	71.93	71.07	0.86
Cleveland	69.90	68.50	1.40
Columbus	71.93	71.94	−.001
Dayton	71.50	70.96	0.54
Toledo	71.99	72.11	−0.12
Youngstown	71.47	70.61	0.86
Suburb			
Akron (balance of Summit Cty.)	74.17	74.93	−0.76
Cincinnati (balance of Hamilton Cty.)	74.40	75.12	−0.72
Cleveland (balance of Cuyahoga Cty.)	74.65	75.10	−0.45
Columbus (balance of Franklin Cty.)	74.72	75.38	−0.66
Dayton (balance of Montgomery Cty.)	74.84	75.22	−0.38
Toledo (balance of Lucas Cty.)	73.88	74.99	−1.11
Youngstown (balance of Mahoning Cty.)	73.66	74.84	−1.18
Rural county			
Adams	73.43	73.17	0.26
Brown	73.74	73.77	−0.03
Gallia	73.52	72.66	0.86
Hardin	74.52	74.95	−0.43
Harrison	74.02	73.62	0.40
Henry	74.25	74.82	−0.57
Highland	74.27	74.04	0.23
Holmes	76.45	77.16	−0.71
Jackson	71.04	71.56	−0.52
Meigs	73.14	73.55	−0.41
Mercer	73.81	74.37	−0.56
Monroe	76.12	76.55	−0.43
Morgan	73.89	74.39	−0.50
Morrow	74.23	74.08	0.15
Noble	75.29	76.12	−0.83
Paulding	73.78	73.56	0.22
Perry	73.21	73.48	−0.27
Pike	73.74	72.79	0.95
Union	73.51	74.43	−0.92
Vinton	74.01	73.61	0.40
Williams	74.77	75.63	−0.86
Wyandot	74.02	74.52	−0.50

Note: Mean error = −0.16; mean absolute error = 0.56; number overestimated = 13; number underestimated = 23; number of absolute errors in excess of 1.0 year = 3.

A relatively crude method was purposefully used to generate the 1980 P65+ estimates in order to examine the accuracy of the life expectancy values under what might be termed extreme conditions of error. The method involved using 1977 P65+ estimates generated by the U.S. Administration on Aging (Fowles, 1978) to find the average annual rate of change in P65+ between 1970 and 1977 and then using the estimated annual rate of change

to project the 1970 P65+ figures forward 10 years to 1980. These estimated 1980 P65+ values were then used in conjunction with the reported 1980 population for each MSA to obtain the percentage of the population aged 65 years and over. This, along with the reported 1980 crude death rate, was used as input for the life expectancy model. The results, displayed in Table 4, indicate that the use of the estimated P65+ values increased the mean absolute error in life expectancy from 0.77 year to 0.85 year. The number of MSAs in which the absolute error was 1 year or more also increased, from 3 to 5. The ratio of overestimated to underestimated MSAs, however, remained the same, 13/17. Altogether, the estimated P65+ values, even though generated from a technique that could be expected to produce results that are not optimal in terms of accuracy, do not lead to major declines in the model's accuracy in generating life expectancy.

Table 4. Estimated and Actual Life Expectancy by Selected MSA, Where the Estimated Values Rely on Estimates of the Population Aged 65 and Over

MSA	Life expectancy at birth		
	Estimated	Actual	Error
Albuquerque, NM	74.51	73.99	0.52
Appleton–Oshkosh, WI	75.53	75.72	−0.19
Baton Rouge, LA	73.13	72.66	0.47
Bismark, ND	76.28	71.97	4.31
Buffalo, NY	72.87	73.28	−0.41
Charlottesville, VA	74.15	73.20	0.95
Columbus, GA–AL	72.07	70.98	1.09
Denver–Boulder, CO	75.04	75.31	−0.27
Erie, PA	72.05	72.28	−0.23
Fort Lauderdale–Hollywood, FL	79.42	73.94	5.48
Glens Falls, NY	73.02	73.47	−0.45
Harrisburg, PA	72.83	83.32	−0.49
Jackson, MI	73.01	72.06	0.95
Kansas City, MO–KS	73.16	73.19	−0.03
Lancaster, PA	73.89	74.57	−0.68
Lincoln, NB	76.05	76.70	−0.65
Madison, WI	76.22	76.43	−0.21
Minneapolis–St. Paul, MN	75.23	75.88	−0.65
New Brunswick–Perth Amboy–Sayreville, NJ	73.35	73.89	−0.54
Northeast PA	73.77	72.95	0.82
Parkersburg–Marietta, WV, OH	73.43	74.05	−0.62
Pittsfield, MA	66.13	68.04	−1.91
Reading, PA	74.71	74.18	0.53
Rock Hill, SC	72.68	71.63	1.05
San Angelo, TX	74.52	74.01	0.51
Seattle–Everett, WA	74.73	75.34	−0.61
Springfield, MO	75.21	75.49	−0.28
Terre Haute, IN	73.26	73.12	0.14
Vallejo–Fairfield–Napa, CA	74.59	75.04	−0.45
Wichita, KS	74.72	74.70	0.02

Note: Mean error = 0.27; mean absolute error = 0.85; number overestimated = 13; number underestimated = 17; number of absolute errors in excess of 1.0 year = 5.

Discussion

One advantage of the regression approach over the life table approach is that the construction of a life table is restricted by small (even zero) numbers of both deaths and population in specific age groups for substate areas. As a consequence, the stochastic variability of age-specific death rates for a small area population reflects sources of instability that are neither manifested in the crude death rate nor in the age-specific death rates of a large population (Manton and Stallard, 1981:217). Thus even when life expectancy can be generated for a small area from a life table, it is often based on "smoothed" age-specific death rates. The regression approach does not require the same degree of smoothing and is not subject to the same level of stochastic variability affecting life tables for small areas. In addition, the model appears to generate relatively accurate life expectancy estimates for counties and their aggregates in noncensus years.[5]

Some caveats are also in order. For example, the model consistently overestimates life expectancy of the southern MSAs in the MSA test data. Whether this would hold for all counties and their aggregates in the South is not known at this time but it suggests that it may be appropriate to consider the construction and use of region-specific models. Similar warnings exist for the use of the state-based model for estimating life expectancy in central cities and suburban areas.

Even with these caveats, the advantages of the regression approach outweigh its disadvantages, and it would allow researchers and administrators at many levels—local, state, and national—to develop life expectancy information. Moreover, it can be used with *published* data, rather than requiring machine-readable data files, which greatly expands the number of potential users. Further, it also requires little, if any, training to implement, which also promotes a wider range of users than that expected for the life table approach.

The results of this test strongly suggest that the estimation technique is a viable means of obtaining life expectancy information for substate areas.

Notes

[1] The possibility that heteroscedasticity and spatial autocorrelation may have affected the model was examined and found to be not likely. In regard to heteroscedasticity, a residual plot against the estimated life expectancy showed no systematic change. Examining the possibility of spatial autocorrelation, the two-tailed Durbin–Watson results indicated that the null hypothesis of no autocorrelation should not be rejected.

[2] The actual and estimated values, which are not shown to conserve space, are available from the author.

[3] Ohio was selected primarily for its convenience (all of the data needed to construct life tables were readily available), but it is also representative of a substantial portion of the country, namely the North Central and Northeast regions. The suburban area of each city is the balance of county area associated with each city. This definition is not exact (e.g., Youngstown is primarily in Mahoning County but its corporate boundaries extend into a little portion of Trumbull County), but it is a consistent way to approximate suburban areas. A rural county is one that is not part of an MSA and in which no single incorporated place has a population of 10,000 or more.

[4] The 1980 death data were derived by using a three-year mean of deaths reported for the period 1979–1981. In 10 of the 22 rural counties, the three-year total number of deaths was less than 700, which may produce some stochastically based fluctuation in the life expectancy values associated with the life tables for these 10 counties.

[5] The raw Medicare enrollment figures, available annually from the Social Security Administration, can be corrected for duplication and adjusted for underenumeration of the population aged 65 years and over by using procedures developed by the U.S. Bureau of the Census (1977:74–76). Direct estimates can be obtained from reports published by the Administration on Aging (e.g., see Fowles, 1978). Further, as stated earlier, at least some State Demographic Centers annually publish county

estimates of both the total population and the population aged 65 years and over (e.g., Washington, 1985:3–5, 12). I recommend, however, that the model not be used indiscriminately with "estimated" population data until more complete accuracy tests are conducted, a task beyond the scope of the present article.

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