

THE PROBLEM OF PRECISION IN MORTALITY DATA  
DERIVED FROM DEMOGRAPHIC SURVEYS: A  
PROPOSED SOLUTION

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*Introduction*

Demographic surveys are highly useful to developing nations. These undertakings may provide high quality data at low cost. They are 'particularly valuable as a means of obtaining vital statistics where civil registration (is) non-existent' (U.N., 1971). As a result, a substantial number of countries have conducted such a survey, e.g., seventeen around 1971 (U.N., 1971).

An important goal of some demographic surveys has been the collection of age-specific mortality data for the calculation of age-specific mortality rates. These rates, of fundamental importance to population projection analysis and concomitant social and economic planning, are the main concern of this paper.

To be optimally useful, data collected in any manner for any purpose must be both accurate and precise.

Accuracy is a quality dependent upon error. Data which contain many errors are inaccurate; data free from error are accurate. For example, let us consider a datum used in calculating an age-specific mortality rate: a death. To be accurate, this datum, of course, must account for a real death. In addition, the placement of the datum in an age category must be correct. Finally, the death accounted for must necessarily have occurred to a member of the population at risk under observation. Given a limited budget for the collection of age-specific mortality data, accuracy is inversely related to the number of data collected. The fewer the data, the more the survey staff can spend on collection and investigation of each one to guarantee its accuracy. Thus, in the case of vital data such as age-specific deaths, accuracy is inversely related to the size of the population at risk. This fact is well known, and holds a central position in the rationale for undertaking demo-

graphic surveys (as opposed to much larger data collecting operations). (See U.N., n.d. p. 44.)

Precision is a quality dependent upon both the nature of the phenomenon being measured and the tool used to measure it; at issue is the crudeness of measurement. A very crude measurement (which incidentally may be very accurate) is imprecise; a very fine measurement is precise. For example, let us consider a quality of the environment which a demographic survey team may undertake to measure: an age-specific value of the force of mortality which, say, is equivalent to .001 per year (or 1 death per 1000 population at risk per year). To measure this force precisely requires the observation of at least 1000 people for a period of one year. Any smaller population at risk *cannot* yield mortality data such that a force of mortality of .001 per year may be calculated. One death in a population at risk of 500 observed for one year, for example, would yield an age-specific mortality rate of .002 per year, double the rate actually being measured. As deaths occur in units, the only smaller rate achievable from this population for one year is 0.0, if no deaths occur. Now, .002 may be a perfectly *accurate* death rate. However, it is a crude representation of the actual force of mortality, .001. Thus, in the measurement of age-specific mortality, precision is directly related to the size of the population at risk.

Therefore, the *precision* with which a demographic survey measures a quality of the environment such as force of mortality is inversely related to the *accuracy* of its tools of measurement such as mortality data. Fortunately, accurate mortality data which yield imprecise rates may be used to derive more precise rates.

Age-specific mortality is a continuous *J*-shaped function of age. Erratic fluctuations in this pattern indicate imprecisely measured rates, if the underlying mortality data are accurate. Thus, anomalous rates of 0.0 indicate imprecision, as do saw-toothed anomalies in the *J*-shaped of the curve. These anomalies are intolerable for most purposes such as population projection analysis.

Methods have been presented in the literature for choosing a smooth *model* mortality schedule from imprecise or incomplete age-specific mortality data. The model data are then used for whatever purpose the empirical data were collected. These techniques are not limited to data collected in demographic

surveys. They have been applied to historical data (Hollingsworth, 1969) and data extrapolated from the present into the future (Shryock and Siegel, 1973, p. 813).

A model mortality schedule is a list of age-specific mortality values which have been derived from analogous empirical mortality schedules, and are expected to apply in many similar situations for other countries or at other times. A model mortality schedule, then, may be considered a generalization of empirical data.

The rationale for the development of several different model schedules is essentially this: Under different environmental conditions with different *mixes* of causes of death, human populations experience age-specific mortality in different ways, which result in differently shaped age-specific mortality curves. Coale and Demeny (1966) have demonstrated that such a shape, or *model* of mortality is relatively stable over a broad range of levels of mortality, or values of expectation of life at birth. By discovering different models of mortality and developing means for deriving mortality schedules of different levels of mortality within these models, one may go a considerable way toward mapping the complete human experience of mortality in these two *dimensions*.

The bulk of model mortality schedules which have been published to date have been prepared by the U.N. (1955), Coale and Demeny (1966), and Brass (e.g., 1968). Not all of the published models are independent of one another. However, the four Coale and Demeny (1966) models, named West, North, East, and South (not to be interpreted as referring to regions of the world as a whole), and the Brass (1968) model for sub-Saharan Africa do compose a set of five relatively independent models.

Model mortality schedules are generally published in "families". A family of model mortality schedules is a set of schedules of different levels of mortality which all conform to a model of mortality. For example, the Coale and Demeny (1966) model West family of schedules all conform to the model West shape, but range in expectation of life at birth (for females) from 20.00 to 77.50.

Using a number of families of model mortality schedules, one may find the model mortality schedule which most closely fits a set of empirical data. This model schedule may be consi-

dered a close approximation of the actual age schedule of the force of mortality underlying the empirical data. A number of techniques for linking empirical mortality data to model data have been presented in the literature by, for example, Coale and Demeny (1966), the U.N. (1967), Brass (1968), and Carrier and Goh (1972). Each of these techniques has been designed with empirical age-specific mortality data of particular precision and completeness in mind. (By completeness, we refer to the completeness with which the age data include all age categories.)

The authors of this paper have recently presented an additional technique which may be used with empirical mortality data of any extent of precision and completeness. However, in comparison to the other techniques referred to above, ours is especially useful for the type of mortality data one would expect to result from a demographic survey, relatively complete, relatively accurate, but lacking optimal precision.

Our technique is built around a closeness of fit statistic from the family of statistics referred to as maximum likelihood, or maximum likelihood estimator, statistics. We use the statistics in conjunction with a number of families of model mortality schedules, such as the four Coale and Demeny (1966) model families. The statistic is used to compute the fit between a set of empirical data, namely, an age schedule of population at risk and an age schedule of observed deaths, and each model schedule selected for comparison. When we compute a value of closeness of fit we treat the model mortality schedule as a hypothetical force of mortality which might have been experienced by the empirical population at risk. The value of closeness of fit is actually the probability that *had* the force of mortality represented by the model schedule acted on the empirical population at risk, the empirical age schedule of deaths *would have* resulted. The model mortality schedule which produces the highest probability value is the closest-fitting schedule.

The reliability of our statistic varies according to the age structure of the population at risk, and its overall size. By using a Monte-Carlo type technique (to be described later), a computer can inexpensively produce reliability values for each application of our statistic. We think this capability should be useful for the planner of a demographic survey. With a *rough* idea of the age structure and mortality level of a population to be surveyed, the planner can compute the sizes of population

at risk necessary to achieve different levels of reliability with the maximum likelihood statistic.

In the remainder of this paper we shall illustrate our method with demographic survey data generated by Madigan (1971) in the Philippines, namely, mortality data collected for urban females in Misamis Oriental. Great pains were taken by Madigan's team to provide complete, accurate sex-age-specific mortality data. Not unexpectedly, however, imprecise sex-age-specific mortality rates resulted.

The anomalies in age-specific mortality rates illustrated by one of Madigan's empirical mortality schedules graphed in Figure 1 led him to substitute model for empirical data. He states, "The observed rates obviously labor under the effects of random variation due to time sampling. Unevenness will be found in the curves of mortality if the observed rates are plotted on graph paper and a line drawn connecting these points" (Madigan, 1971: 133).

Madigan chose to work with Coale and Demeny (1966) model mortality schedules and stable age distributions in converting his mortality data to more precise form. It may be useful to compare the general characteristics of the technique with which he worked with our own.

Madigan (1971) described the conversion technique he chose as follows:

These rates were derived by redistributing the observed rates, corrected by the Chandra Sekar-Deming estimate of missed cases (which was distributed by age groups in proportion to the observed deaths), according to percentages of total deaths occurring in each of the different age groups of the appropriate Coale-Demeny Model-West life tables already referred to. The appropriate model table for each area and sex set of rates was determined by the birth, death, and natural increase values found in the observed sex population.

(p. 133)

We feel that the conversion technique described by Madigan does not make optimal use of the data which he so painstakingly collected. In using the above technique, Madigan was forced to assume that the age distributions of his empirical populations at risk were stable. This assumption is crucial in

choosing the model schedule, and then in redistributing deaths according to a stable age distribution based upon it. Figure 2 illustrates the difference between the age structure of the population at risk which experienced the mortality rates graphed in Figure 1, and the stable age distribution which Madigan's technique assumed it to be. Clearly, the assumption of stability, and the results based upon it, are tenuous for this particular population.

More importantly, however, the technique Madigan employed did not make use of the rich information at his disposal for selecting model data. Instead, crude rates were used. Madigan's final age-specific mortality estimates simply are not related to the age-specific mortality data he collected. Merely the total number of deaths, births, and the age-specific population at risk were used to produce the final estimates of mortality.

Our technique both avoids tenuous assumptions such as stability in age structure, and uses the full richness of age-specific mortality data in making the choice of closest fitting model data. Unlike the one chosen by Madigan, our technique does not depend, *a priori*, on the choice of a particular family of model schedules. In fact our statistic informs that choice, when used with a number of families of model schedules, thus locating the position of an empirical data set in *two* dimensions of mortality (level and model), versus *one* (level).

### Methods

The likelihood statistic underlying our technique has been discussed at length previously (Fulton and Ristow, 1975). Thus, we do not describe it fully here. Rather, we present a working formula which has been designed for ease of computing:

$$(1) C = \sum_{e=1}^I nDx_i \ln(n_i Mx_i) + (n_i Nx_i - n_i Dx_i) \ln(1 - n_i Mx_i),$$

where:  $C$  is the value of closeness of fit between the model mortality schedule and the empirical mortality data.

$i$  identifies age group  $i$ , where  $i$  varies from the first chronological age group (e.g., 0-1 year of age) to the last age group observed,  $I$ .

$n_i D_{x_i}$  is the number of deaths observed in the population of age group  $i$ .

$n_i M_{x_i}$  is the age-specific mortality rate for age group  $i$  in the model mortality schedule which is being compared to the empirical data.

$n_i N_{x_i}$  is the number of people at risk of dying in age group  $i$ .

$x_i$  is the age of the youngest members of age group  $i$ .

$n_i$  is the width of the age group  $i$ . Thus age group  $i$  spans the ages  $x_i$  to  $x_i + n_i$ .

The value of  $C$  defined above is a summary value of closeness of fit over all age categories. Actual computations other than this final summation proceed by age category. Within an age category we are interested in four values which are combined in formula 1:

- 1)  $nDx$ , the number of deaths occurring to the population at risk,
- 2)  $\ln(nMx)$ , the natural log of the model mortality rate,
- 3)  $nNx-nDx$ , the number of survivors left of the population at risk at the end of the observation period, and
- 4)  $\ln(1-nMx)$ , the natural log of 1.0 minus the model mortality rate.

A work sheet which might be set up for computing the value of  $C$  is presented as Table 1. The empirical data in Table 1 have been reconstructed from Madigan's (1971) report. The model schedule used is Coale and Demeny's (1966) model West, level 20. Notice that the calculations are those which might easily be made on a good pocket or desk calculator.

If the analysis is to proceed by hand, one work sheet is needed for each model mortality schedule. It is recommended that model schedules be used one model family at a time, finding the closest fitting model schedule within a family before proceeding to the next.

Formula 1 yields negative values of  $C$  exclusively. Therefore, in comparing the values of  $C$  for different model schedules, the sign of the values may be disregarded.

The lower the value of  $C$ , the closer the fit between the model schedules in question and the empirical mortality data. If one computes values of  $C$  for an entire family of model schedules, one finds a unique minimum value of  $C$  indicative of the schedule most closely fitting the empirical data. (An example of such a set of  $C$  values is presented in Table 2 for Madigan's urban female data and Coale and Demeny's model West family of mortality schedules.) This means that one need not compute  $C$  values for an entire model family of schedules.

Before computing  $C$  for any model schedule within a family, we estimate the level of the schedule which seems most likely to produce the lowest value of  $C$ . Then we compute the value of  $C$  for the schedule in the same family which is of the next higher level. If this value of  $C$  is higher than the first, we repeat the procedure for the schedule in the family which is of the next lower level (to that of the first schedule). The idea is to "bracket" the lowest value of  $C$  which the family of schedules will yield with two higher levels of  $C$ .

It is not difficult to derive a reasonable estimate for the level of the schedule which will most closely fit the empirical data. This estimate may be made "by eye" using empirical mortality data from an age category which yields relatively precise data, i.e., one with a large population at risk and a relatively large mortality rate, e.g., the age group 1-4 years. The choice of this age group may vary according to the age structure of the population at risk. When the age group is chosen, its empirical mortality rate is computed and compared with the model mortality rates for the same age group found in a family of model schedules. The model schedule whose age rate in question most closely matches the empirical rate is chosen as the rough estimate of the closest fitting models schedule within that family.

Once the closest fitting schedule within one family of schedules is found, it is not necessary to repeat the initial estimation procedure for the remaining model families. Instead, one begins the search for the closest fitting model schedule within these families with the schedule of the level which proved to be closest fitting in the first family analyzed.

Hence, relatively few comparisons between empirical and model data (using formula 1) need be made to locate the closest fitting model schedule from among a number of families



of model schedules. This is the model schedule which yields the smallest value of  $C$ .

Even though similar model schedules are employed, values of  $C$  computed for different sets of empirical data are not strictly comparable, due to a simplification made in deriving formula 1. This simplification allows much greater ease in computation, and does not affect comparisons of values of  $C$  computed for the *same* set of empirical data. As values of  $C$  need not be compared across sets of empirical data for the function presented in this paper, the simplification in formula 1 should not restrict the researcher whose primary interest is finding closest fitting model data to individual sets of empirical data. A more formal version of formula 1 is presented in Fulton and Ristow, 1975.

Once a closest fitting model schedule has been chosen for a particular set of empirical data, the reliability of the choice may be found, if a high speed computer is available. One possible reliability test makes use of the Monte Carlo technique, which is relatively inexpensive.

The technique we suggest requires as input the age-specific population at risk and the model schedule which most closely fits the empirical mortality data. Using the Monte-Carlo technique, empirical mortality data for one year's observation are simulated by exposing each member of the population to the probability of dying in one year's time for the appropriate age group (approximated by  $nM_x$ ). A random number is drawn for each exposure from a pool of random numbers which are evenly distributed between 0.0 and 1.0, the minimum and maximum probability of dying. The random number is compared with the probability of dying. If the random number exceeds the probability of dying, the exposed member of the simulated population at risk survives the period of observation. If not, the member does not survive. This process is repeated for every member of the population to produce one set of simulated empirical mortality data. A number of sets, e.g., 20, are produced. These sets represent a sample of empirical regime and population at risk. The empirical data are then processed to find the closest fitting model data from a number of families of model data, to see how reliable the process is in indicating the actual model mortality regime which underlies the simulated data. In other words, we use the model mortality schedule to represent the mortality regime experienced by the real population at risk in the real world. Thus, we

indirectly test, through simulation, the reliability of the technique with the actual population at risk and a close representation of the actual mortality regime.

Reliability in the choice of model is distinct from reliability in the choice of level. Reliable choice of model is an all-or-nothing thing, as models are not ordered on a continuum. Levels, however, are. Hence, reliable choice of level may be expressed on a continuum such as: 1/ choice of level correct, 2/choice of level correct to within one level of mortality (equivalent to 2.5 years expectation of life at birth for the Coale and Demeny schedules), and 3/ choice of level correct to within two levels of mortality.

The reliability test outlined above may be useful to the demographic survey planner who has access to a high speed computer. The reliability of our technique for population with estimated age structure and mortality regime may be tested with alternate sample sizes of total observed population at risk. These tests may be used to inform the planner of the adequacy of various sample sizes for producing reliable estimates of age-specific mortality. Of course, the reliability of this procedure itself depends on the extent to which the estimated age structure of population at risk and estimated mortality regime adequately represent the actual age structure of the population and the actual mortality regime it experiences. However, initial tests of our proposed statistic (Fulton and Ristow, 1975) have indicated that its reliability does not change radically with moderate changes in age structure of population at risk or with moderate differences in level of mortality.

We applied the methods outlined in this section of the paper to Madigan's (1971) mortality data for urban females, yielding new estimates of age-specific mortality, reliability estimates for the same, and alternate sizes of observed population at risk needed to produce results of varying reliability. Our results are presented in the next section of the paper.

### *Results*

Using the likelihood statistic, Madigan's (1971) empirical mortality data for urban females were compared with the four families of Coale and Demeny (1966) model mortality schedules, West, North, East, and South. The closest fitting schedule is model West, level 20. Level 20 corresponds to an

expectation of life at birth of 67.5 years.

Reliability results are presented in Table 3. For technical reasons the population(s) at risk in the simulation trials included all age groups between the ages of 0 and 64, only. The figure 11,320 represents the approximate number of urban females between the ages of 0 and 64 surveyed by Madigan (1971). The remaining three figures for size of population at risk are multiples of 11,320, namely, 2x, 5x, and 10x, or 22,640, 56,600, and 113,200, respectively.

Recall that the reliability of the likelihood statistic is specific to the population under consideration, e.g. urban females, Misamis Oriental.

Referring to Table 3, note that the likelihood statistic was able to distinguish the correct model of mortality underlying simulated data sets of size 11,320 in 11 out of 20 trials, or 55 percent of the time. This figure indicates "fair" reliability. For reference, a 25 percent success rate would be attributable to chance alone, given four models to choose from. The performance of the statistic in choice of model remained the same with simulated data sets of size 22,640. However, performance did increase for simulated data sets of size 56,600, and then again for simulated data sets of size 113,200, with 85 percent success and 100 percent success, respectively.

The reliability of the statistic in regard to choice of level likewise increased with increasing sample size. For simulated data sets of size 11,320, the reliability of the statistic in choice of level is good. Ninety-five percent (19 out of 20 trials) resulted in choice of level within one level of the correct underlying mortality regime. (One level corresponds to 2.5 years expectation of life at birth.) Correct choice of level was made in 11 of 20 trials, or 55 percent of the time. For simulated data sets of size 22,640, level was correctly chosen 70 percent of the time (in 14 of 20 trials). For data sets of size 56,600, this figure jumps to 85 percent (17 of 20 trials). Finally, for data sets of size 113,200, the statistic chose correct level in all 20 trials. In no trial did the statistic choose a closest fitting level beyond 2 levels of the correct underlying mortality regime.

### *Discussion*

Madigan (1971) substituted model-derived mortality data

for the empirical data collected from urban females. However, nowhere does he specify the exact model schedule used for this purpose, except to say that it belongs to the West family of Coale and Demeny (1966). From information provided in his report (1971), we deduce that the level of mortality of the model West schedule in question is 22, which corresponds to an expectation of life at birth of 72.5 years.

Our results support Madigan's *a priori* choice of model West data. The likelihood statistic makes the same choice. However, the reliability of this choice is less than good.

Our results do not support the choice we have attributed to Madigan (above) in regard to level of mortality. The difference between his choice of level and ours (20) is 2 (levels), equivalent to a difference in expectation of life at birth of 5.0 years. Further, the results of our reliability trials imply that the likelihood statistic should make a two level error (with the urban female data) only a very small percentage of the time (5 percent in 20 trials). Thus, it is possible that Madigan's analysis has resulted in an underestimation of the force of mortality experienced by the population in question.

More important than the possibility of error, however, is the fact that Madigan's choice of technique did not facilitate estimation of the reliability of his choice of model data. Thus, it is difficult to judge which set of data is more representative of the actual force of mortality experienced by the urban females on Misamis Oriental, the raw data, relatively accurate but burdened with imprecision, or the derived set, of unknown accuracy but less anomalous.

Further, on the basis of Madigan's (1971) results, it is difficult to assess the adequacy of the sample size used in his survey, except to say that the precision of the mortality data would have been better had the sample size been larger. Our results demonstrate that increasing the size of the population at risk by a factor of 2, a large increase, would have yielded data of only slightly improved precision. Locating the position of the data in the dimension of model would not have become perceptibly easier (more reliable). Locating the position of the data in the dimension of level would have become slightly easier, though probably not enough to warrant a doubling in certain survey costs.

Thus, we hope that our technique contributes to the work of those whose task is estimating the mortality regime experienced by small populations, by informing the process of survey planning, and by aiding in the correction of imprecise data. Toward this end the authors of this paper have prepared computer programs capable of performing much of the analysis presented above. The programs have been written in FORTRAN IV and tested on an IBM 360/67. However, they are small in size and should not require much revision to perform efficiently on smaller machines. Listings are available on request.

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Table I. — Worksheet for the Computation of  $C$ .

Age Category	$nD_x$	$nN_x$	$nM_x$	$1-nM_x$	$\ln(nM_x)$	$nD_x \ln(nM_x)$	$nN_x - nD_x$	$\ln(1-nM_x)$	Age-specific values of $C$
0-1	7	310	.04173	.95827	-3.177	-22.239	303	-.04263	-35.156
1-4	11	1260	.00320	.99680	-5.745	-63.195	1249	-.00321	-67.204
5-9	0	1300	.00100	.99900	-6.908	0.0	1300	-.00100	- 1.300
10-14	0	1250	.00078	.99922	-7.156	0.0	1250	-.00078	- 0.975
15-19	3	2150	.00126	.99874	-6.677	-20.031	2147	-.00126	-22.736
20-24	0	1660	.00174	.99826	-6.354	0.0	1660	-.00174	- 2.888
25-29	0	1010	.00207	.99793	-6.180	0.0	1010	-.00207	- 2.091
30-34	0	710	.00244	.99756	-6.016	0.0	710	-.00244	- 1.732
35-39	4	500	.00301	.99699	-5.806	-23.224	496	-.00301	-24.717
40-44	0	360	.00389	.99611	-5.549	0.0	360	-.00390	- 1.404
45-49	3	260	.00540	.99460	-5.221	-15.663	257	-.00542	-17.056
50-54	4	230	.00784	.99216	-4.849	-19.396	226	-.00787	-21.175
55-59	4	180	.01153	.98847	-4.463	-17.852	176	-.01160	-19.894
60-64	7	140	.01807	.98193	-4.014	28.098	133	-.01824	-30.524

(Total)  $C = -248.852$

Table 2. — Set of  $C^a$  Values, Summarizing Closeness of Fit between Coale and Demeny (1966) Model West Family of Model Mortality Schedules and Empirical Mortality Data from Urban Females, Misamis Oriental (1971).

Level of Mortality	Expectation of Life at Birth	C
1	20.0	401.6
2	22.5	346.7
3	25.0	301.6
4	27.5	263.7
5	30.0	231.2
6	32.5	203.0
7	35.0	178.4
8	37.5	156.7
9	40.0	137.5
10	42.5	120.5
11	45.0	105.3
12	47.5	91.8
13	50.0	79.8
14	52.5	69.2
15	55.0	59.8
16	57.5	51.8
17	60.0	45.3
18	62.5	40.4
19	65.0	37.3 <sub>b</sub>
20	67.5	36.5
21	70.0	38.6
22	72.5	43.8
23	75.0	53.8
24	77.5	70.5

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a — Values of  $C$  derived using *complete* version of likelihood statistic, not computing formula. Both versions of  $C$  produce a unique minimum value per model family which indicates the same closest fitting model mortality schedule.

b — Minimum value of  $C$  for the model West family of model mortality schedules.

Table 3. — Ratio of Successes to Attempts at Finding Correct Model and Level of Mortality Underlying Simulated Mortality Schedules, Using the Likelihood Statistic with Coale and Demeny Model Mortality Schedules.

Size of Population at Risk		Ratio of Successes to Attempts	Percent Successful Attempts
11,320	Model Chosen Correctly	11/20	55
	Level Chosen Correctly	11/20	55
	Level Chosen Correctly within One Level <sup>a</sup>	19/20	95
	Level Chosen Correctly within Two Levels <sup>b</sup>	20/20	100
22,640	Model Chosen Correctly	11/20	55
	Level Chosen Correctly	14/20	70
	Level Chosen Correctly within One Level	20/20	100
	Level Chosen Correctly within Two Levels	20/20	100
56,600	Model Chosen Correctly	17/20	85
	Level Chosen Correctly	17/20	85
	Level Chosen Correctly within One Level	20/20	100
	Level Chosen Correctly within Two Levels	20/20	100
113,200	Model Chosen Correctly	20/20	100
	Level Chosen Correctly	20/20	100
	Level Chosen Correctly within One Level	20/20	100
	Level Chosen Correctly within Two Levels	20/20	100

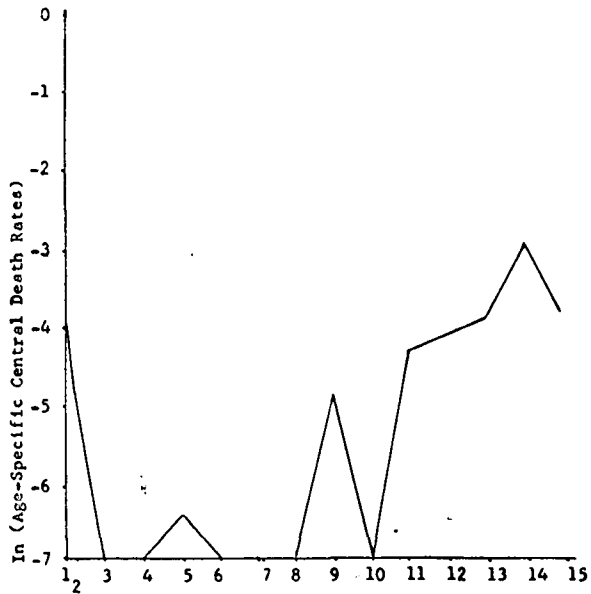
a — This distance equivalent to 2.5 years expectation of life at birth.

b — This distance equivalent to 5.0 years expectation of life at birth.



Age Group<sup>a</sup>

Figure 1. — Natural log of age-specific central death rates, urban females, Misamis Oriental, September 1 — December 31, 1971.



- a — 1 : 0-1 year  
 2 : 1-4 years  
 3 : 5-9 years  
 4 : 10-14 years  
 5 : 15-19 years  
 6 : 20-24 years  
 7 : 25-29 years  
 8 : 30-34 years  
 9 : 35-39 years  
 10 : 40-44 years  
 11 : 45-49 years  
 12 : 50-54 years  
 13 : 55-59 years  
 14 : 60-64 years  
 15 : 65 years and over

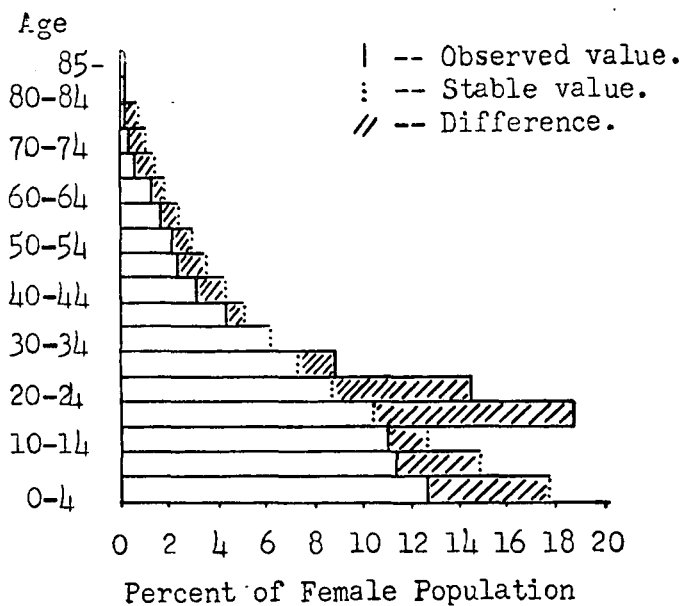


Figure 2. — Comparison: Age structure of urban females, Misamis Oriental, November 1, 1971, with age structure of table population chosen to represent urban females, (Coale and Demeny, Model West, Level 22, Growth Rate equivalent to 35 / 1000 / year.)