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Demographers for many years have attempted to predict future trends in fertility and population, but have generally failed. Unfortunately, even as the science of demography has matured and its methodology become more sophisticated, the accuracy of fertility and population projections has not improved. Indeed, many modern projections are substantially worse than early projections made with sometimes crude techniques. This lack of accuracy coupled with the increased use of population projections in planning processes which result in the expenditure of substantial public and private funds suggests that improvements in projection methodology should be thoroughly investigated and that the error in projections should be quantified. The inclusion of distributional information with projections, either in the form of subjective probability estimates or explicit variance estimates, would immediately tell a user how much confidence to place in a projection and would make the projection more useful.

In developed countries, the component of population growth which has proved hardest to predict—fertility—has also been the major determinant of population growth. The accuracy of early projections can be attributed to the fact that fertility changes were very slow and gradual; however, this is no longer true as there seem to be swings of fairly large amplitude in fertility.

The problem of predicting long term trends in fertility for modern post-transition populations may not be as difficult as it has been for the past 50 years, however. It is possible to argue that in populations which have completed the demographic transition, there are no secular trends in fertility. With the completion of the adjustment of fertility to declining mortality, fertility in the future is likely to fluctuate around replacement levels.

Even if a model which included fertility fluctuating around replacement levels were accepted and brought into use, demographers would need some knowledge of the frequency and amplitude of the cycles in order for the model to be helpful for prediction purpose. The existence of such fertility cycles has been attributed to factors such as age structure which are internal to demographic systems (e. g. Easterlin and Condran, 1975) and to outside disturbances such as economic influences (e. g. Easterlin, 1973) mixed with environmental constraints (Lee, 1974b). The presence of such cycles has been empirically verified; and they could aid greatly in predicting fertility.

This conceptualization of fertility as fluctuating around a fixed level (replacement level) suggests that time series techniques could be profitably employed in studying fertility processes. Time series methods may not solve the problem of accurate trend prediction but the methodology can aid in quantifying the error process. Time series methods are wellsuited for solving the problem of how much of a deviation from trend can be regarded as a fluctuation, not necessarily invalidating the entire forecast. With the addition of models for the variance of projections, the distributional information on population projections required for improved planning can be supplied in the form of confidence intervals.

1. Methods and Data

The projections reported in this paper were made with the classical discrete model of population dynamics, $\underline{X}_{t+1} = \underline{A}_t \ \underline{X}_t$. In this model, \underline{X}_t is a column vector with each element representing the number of individuals in an age group at time t. The matrix \underline{A}_t represents the survival of population members from one age group to the next and the entrance (birth) of new members into the first age group $X_{t,1}$.

The variance calculations are based on the random transition matrix model of Sykes (1969) which assumes that the transition matrices, the \underline{A}_{t} 's, form a sequence of random variables:

$$\underline{X}_{t+1} = (\underline{A}_t + \underline{\Delta}_t) \underline{X}_t ; t = 0, 1, \dots$$
 (1.1)

where $\underline{\Delta}_t$ is a square matrix of random variables with the properties

$$E[\Delta_t] = 0$$
; $E[(\Delta_{iks} \Delta_{jlt})] = \sum_{st}$

and \sum_{t} is a singular variance-covariance matrix. With conditional arguments, it can be shown that the mean of the random process, $\underline{\mu}_t$, is identical to the deterministic process. The variance, \underline{V}_t , is then the sum of the one-step innovation variance, \underline{M}_t , and the weighted sum of the variance from the previous steps

$$V_{t} = \underline{M}_{t-1} + \underline{A}_{t-1} - \underline{V}_{t-1} - \underline{A}_{t-1}$$
(1.2)

where

 $\{ m_{tij} \} = \left\{ \sum_{\alpha,\beta} Cov(\Delta_{ti\alpha}, \Delta_{tj\beta}) (v_{t\alpha\beta} + \mu_{t\alpha}\mu_{t\beta}) \right\}$

The confidence interval for births can be shown to be (Schweder, 1971):

$$|X_{t1} - \mu_{t1}| \le \sqrt{V_{t11}}$$
 (1.3)

where is the percentage point in the X-distribution with degrees of freedom equal to the rank of \underline{V}_{t} .

These basic equations are used to compute the projections but projected values for the parameters must be obtained by other means. The methods of time series analysis, in which the behavior of any variable over time is characterized by relationships to past values of the variable itself, can be used to predict values of the birth rates in \underline{A}_t , the b_j's, and the struc-

ture of the residuals can be used for ∠t. The data used to fit the time series models are 36 series of annual central age-specific birth rates, ages 14-49 for 55 years, 1917-1971 (Whelpton and Campbell, 1960 and annual volumes of <u>U. S. Vital Statistics</u> from 1964). From the projected values of the annual central birth rate, f_j , the values of b_j are obtained by

$$b_j = (L_0/2 c_0) (f_j + s_j f_{j+1}) \cdot$$

Because the major emphasis of this study is fertility, the values for survival rates were computed from actual life tables for 1950-1971 and from Census Bureau projections for the years 1972 and later. Annual immigration of 400,000 was assumed. For the initial population vectors, \underline{X}_{o} , data from the 1950 and 1960 Census were used; see Passel (1976) for more detail concerning data sources.

2. Time Series Methods and Results

The time series methods of Box and Jenkins (1970) were used to fit autoregressive, integrated, moving average (ARIMA) models to the birth rate series. Following their notation, the general form for a p-th order autoregressive, d-th order integrated, q-th order moving average model, also referred to as a (p,d,q) ARIMA model, is

$${}^{\phi}{}_{p}(B)\nabla^{d}f_{t} = {}^{\theta}{}_{0} + {}^{\theta}{}_{q}(B)\epsilon_{t}$$
(2.1)

The identification, selection, and estimation of appropriate time series models for the series of age-specific birth rates was accomplished following the methods suggested by Box and Jenkins (1970, Chapter 6).

The selection of an appropriate model for a given series depends on two major factors: 1) the uses of the model and 2) the nature of the series itself. All of the ARIMA models selected for fitting to the birth rates series included first or second differences. No unintegrated (i.e. d=0) models were selected for two reasons. First, examination of the autocorrelation functions for the series of age-specific and ageparity-specific birth rates suggests that practically all of the series, particularly those not at the older reproductive ages, are nonstationary. Second, and more important, the behavior of projections made using unintegrated models does not adequately portray the behavior of the birth rates. Projections made from undifferenced time series models decay exponentially to the mean of the series. There is no reason to impose this type behavior on the birth rate or probability projections. Furthermore, in every case, at least one integrated model produced a better fit than any unintegrated model. Differencing of higher than second order was not necessary to achieve apparent stationarity for any of the series.

The best fitting model for each age-specific birth rate was determined by the so-called portmanteau test, Q (Box and Jenkins, 1970:291), residual variances, and parsimony. Generally, for each birth rate series, the model with the smallest value of Q was chosen for the projections. If there were two or more models with small and approximately equal values of Q, the one with the smallest value of the residual variance, σ_e^2 , was chosen.

variance, σ_c^2 , was chosen. Of the 36 series of age-specific rates, all but 7 were fitted with models which yielded values of Q that had probabilities of occurrence of 0.70 or larger; none had a value smaller than 0.24. Box and Jenkins (1970:292-3) treat values of Q with probabilities of occurrence in the range 0.25 to 0.10 as indicative of some model inadequacy. Thus, all of the models presented in Table 1 fit the data quite well.

The fitted models are quite parsimonious. Only 8 of the series required second differencing to produce an adequate fit; only one of these (age 30) was at an age which contributes a substantial amount to overall fertility. Only 5 series (ages 30, 37, 39, 42, and 43) required four autoregressive terms, two degrees of differencing and two degrees in the AR coefficients. Seventeen series required moving average terms to provide an adequate fit but only one (age 35) required a second order MA term.

A further indication of the adequacy of the selected models is provided by the similarity of form and content shown by models for nearby ages. It is possible that other more complex models may provide a better fit for some of the series but this seems unlikely in view of the general similarity in form and the tendency for overfitted models to produce worse results. Thus, the models presented in these tables, i.e. the parameter values, residuals, and residual variances, are the ones used in the population projections presented in the next section.

3. Results of the Projections

Two basic sets of projections are reported here: 1) starting in 1950 and continuing through 1975; and 2) from 1960 through 1975. The same time series models (Table 1) were used in each case. Thus, the "projection" models are based on data which include values from the projection period. This should lead to improved projections but, as will be seen, the overall quality of the projections is generally poor in spite of this bias toward "good" projections.

The behavior of the projections of the individual series of age-specific birth rates can be characterized by two main features: 1) each series levels off very quickly and 2) the amount of change from the initial value to the final value is relatively small. In order to assess the overall adequacy of the time series models the total fertility rate (TFR) and the projected births will be examined.

3.1 Fertility Projections: 1950-1975 TFR. The behavior of the TFR as projected from the 1950 base year is consistent with the behavior of the individual age-specific birth rates as just described. The projected TFR was essentially constant, staying roughly between 2,900 and 3,000; the oscillations are the result of minor deviations in fertility, mortality, and age structure. The projected value for the first year, 1951, was too low by 9 percent (2,968 vs. the actual value of 3,267) and the projected amount of change from 1950, -123, was in error by 262 percent. (See Figure A and Table 2.) The projection missed the 1950's "baby boom" entirely. By 1957, the peak year for TFR, the projected TFR was 811 points or 22 percent too low (3,760 vs. 2,949). Actual fertility fell after 1957 so that by 1965, the actual and projected TFR

differed by only 47 points or 2 percent (2,928 vs. 2,881). However, the projections again did not predict another major fertility movement the post-1960 decline in fertility. By 1975, the actual TFR was far below the projected value; the actual TFR (1,800) was 1,114 points less than the projected value (2,914) which was 62 percent above the actual TFR.

<u>Births</u>. The accuracy of birth projections made from base year 1950 with age-specific rates is comparable to the accuracy of the TFR projections for the first 15 or so years. Even the projection for the first year, 1951, is substantially in error. The difference between the projection (3,481,000) and the actual births (3,771,000) of 290,000 represents an error of 7.7 percent, a substantial amount for a single year forecast. In fact, the number of births fell outside the 50 percent confidence limits which were 3,481,000 + 192,000 or a range from 3,289,000 to 3,673,000. (See Figure B and Table 2.)

The birth projections remain nearly constant between 3,400,000 and 3,500,000 per year through 1961. Then, the projected number of births begins to increase exponentially. This trend is, unfortunately, almost just the opposite of what actually occurred - an increase in the number of births from 1951 to 1961 followed by a general decline through 1975 (with the exception of 1969-1971). Although the curves of projected and actual annual births cross about 1966, the percentage errors increase again because of the different trend directions. By 1974, the difference between the actual number of births (3,115,000) and the projected number (4,676,000) reached 50.1 percent of the actual births!

The overall inaccuracy of the projected number of births can be seen quite clearly by examining the 50 percent confidence interval, which is +192,000 for the first year of the projection and shows an increase of about + 100,000 for each year of the projection. After only ten years, the 50 percent confidence limits reached \pm 965,000 with the total width of the interval (1,930,000) being over 55 percent of the projected number of births. Even with these very wide limits which increased substantially each year, the increasing trend in the number of births is great enough to keep the actual value above the confidence interval for the first 8 years of the projection; only when the annual number of births levelled off in 1959 and 1960 did it fall within the 50 percent confidence limits.

3.2 Fertility Projections: 1960-1975

The projections from base year 1960 exhibit the same general tendencies as those from 1950. The projected TFR changes little from the initial value and levels off slightly above 3500 thus missing the decline of the 1960's. (See Figure A and Figure B_{\bullet})

4. Discussion and Conclusions

The results indicate that the various projections are neither very accurate nor precise. Projections of births over periods of time as short as 1-5 years miss the actual births by substantial amounts. Over longer periods of

time, 10-25 years, the projections bear practically no relationship to the actual course of events. The variance estimates appear to be quite large, too large in fact to provide useful confidence intervals for users of projections over short, medium, or long range. However, the inaccuracy of the projections, the large variances, and the failure of the actual value to fall within quite large fifty percent confidence intervals do not invalidate the variance models. The size of the estimated variance depends directly on the variances of the birth rates as determined from the projection models for the rates. Likewise, the accuracy of the projections is determined by the birth rate models. Thus, it is possible, even in light of the poor performance of the projections, to draw some meaningful conclusions about the precision of the projections, the variance models, and the method of computing confidence intervals. The variance of the annual births is pri-

marily a function of the variances of the projected birth rates. Projections of birth rates from time series models have variances which increase as the number of intervals (steps) from the origin increases. For the projections in this paper, the 50 percent confidence limits of annual births increase by about + 50,000 to + 150,000 per year. This means that by ten years into a projection, the 50 percent confidence limits for births are about $\pm 1,000,000$ when annual births in this country generally have fallen in the range of 3,000,000-4,000,000. Furthermore, if the projection is carried far enough so that the projected birth cohorts with their large variances reach the childbearing ages, the variances of the next generation of births grow at an explosive rate. After 25 years or less, the 50 percent confidence limits for births could easily include no births. This property of increasing variance with time is logical and should be expected; the ability of demographers to forecast the number of births ten years (or even two years) in the future has proved to be guite limited. However, the magnitude of the variance of births in these projections is too great for practical application.

More precise projections, i.e. smaller confidence intervals, would provide better <u>ex post</u> assessment of projections and better <u>ex ante</u> limits for utilizing population projections. So, what can be done to make the confidence intervals and variances smaller? First, it should be stressed that the large variances found in this research are meaningful in the context of the projection models. The variances represent the actual experience in the United States over a period of 55 years as modelled with time series. So obviously, one way to decrease the variance of the projected births is to use more precise models for projecting the birth rates.

The size of the variance of a projection is a function of the number and size of the variances of the elements of the projection matrix. Thus, the overall variance could be reduced if the number of birth rates in the matrix could be reduced. In a related manner, the variance at lead time t could be reduced if the number of intervals between the origin and t could be reduced. By using 5-year age groupings (7 agegroups instead of 36) and 5-year time intervals, the variances of the projections for middle and long range projections could be reduced substantially.

A reduction in the variance of a projection as a result of increasing the size of the projection intervals and age groups would not be a mere statistical artifact. Small annual fluctuations in birth rates and births are removed by the aggregation. For many purposes, such projections would prove to be very useful. However, in a sense, this would be sidestepping important issues about improving, not the precision but, the accuracy of population projections, particularly over the short run. If the variance would be reduced, the projection models for fertility would still not be adequate.

The blame for the inaccuracy of the projections must be laid on the time series models. The models were fitted to the entire data series, 1917-1971, and were used to "project" points within the limits of the data as used to fit the models yet they still did a very poor job of predicting future values of the birth rates. What, then, went wrong with the projections of fertility and what can be done to improve them? Very little variation was predicted for individual birth rates; the smooth and relatively constant trends can be attributed directly to the properties of the time series models. Most of the year-to-year variation in birth rates is assigned to the random shock or residual term. In the projections these terms become zero so that their effect in the long run (after initially determining the level of the rate) is virtually nonexistent. The actual birth rates, however, are not mainly the result of random variation. Thus, the time series models are not adequate for most prediction purposes and do not model the actual process. However, improved time series models could possibly be useful for one- or two-year projections which could be updated annually.

Over medium and long ranges, the time series models used in this research do not predict trends very well. Essentially, the projected birth rates remain at a constant level close to the original level after four or five years rather than experiencing a prolonged, gradual movement to some, possibly very different, ultimate level. Although the model is based on the whole series, the projected trend and level are based wholly on the last p + d (usually not more than 4) values. Thus, the long range trend is a function of very short range variation and may be substantially different from the actual trend and from trends predicted in other ways.

Over both the short and the long term, the time series models do not do a very good job of predicting fertility (or of estimating the variance). Clearly, more structure than merely the autocorrelation of a series of birth rates itself is necessary to provide reasonable forecasts. Furthermore, it is unlikely that any model based solely on demographic variables such as age, sex, interval since last birth, parity, etc. will yield accurate projections of fertility even in the short run. (Figures A and B show that projections made by adding parity to the models are not substantially different. See Passel, 1976 for more discussion of these results) A great deal of research has been done which demonstrates clearly that social and economic factors exert major influences on fertility. What is needed for accurate fertility (and, consequently, population) projection is a model which incorporates social and economic factors in addition to relevant demographic variables. However, we should not be limited to the usual regression techniques which ignore or suppress the known autocovariance structure of fertility.

A great deal of work in the area of fertility has been done with regression techniques and some with time series analysis (Saboia, 1974; Lee, 1974a), but the techniques have not been used together. However, methods are available which incorporate models of ARIMA processes and simultaneous equation models in such a way as to use regression techniques and time series analysis in estimating and checking the model (Zellner, 1975). Such linear multiple time series models could provide the basis for an integrated system relating social, economic, and demographic variables for providing accurate forecasts of fertility and population as well as estimates of the projection error.

Predicting the future for any purpose is difficult; the future of fertility especially has not proved to be easy to foretell. The methods of time series analysis, although useful tools (particularly for computing confidence limits), have unfortunately not provided an immediate solution to the problem of fertility projection. This does not mean that demographers should abandon the methods of Box and Jenkins. Rather, by combining the work of social demographers (with respect to correlates of fertility), economists (such as Easterlin for theory and Zellner for methodology), and statisticians, the work reported in this paper could be extended so that it might be possible in the not too distant future to predict with a reasonable degree of accuracy not only the short range (1-5 years) course of fertility and population growth, but also the long term (20-50 years) possibilities.

REFERENCES

- Box, George E. P. and Gwilym M. Jenkins, 1970. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.
- Easterlin, Richard A., 1973. Relative economic status and the American fertility swing. Pp. 170-223 in Eleanor Bernert Sheldon (Ed.),
 Family Economic Behavior: Problems and Prospects. Philadelphia: J. B. Lippincott.
- , and Gretchen A. Condran, 1975. A note on the recent fertility swing in Australia, Canada, England and Wales, and the United States. Forthcoming in Migration, Foreign Capital, and Economic Development: Essays in Honor of Brinkley Thomas. Keyfitz, Nathan, 1972. On future population.
- Keyfitz, Nathan, 1972. On future population. Journal of the American Statistical Association 67 (338, June):347-363.
- tion 67 (338, June):347-363. Lee, Ronald D., 1974a. Forecasting births in post-transition populations: stochastic renewal with serially correlated fertility.

Journal of the American Statistical Association 69 (347, September):607-617. _____. 1974b. The formal dynamics of con-

. 1974b. The formal dynamics of controlled population and the echo, the boom, and the bust. Demography 11 (4, November):563-586.

- Passel, Jeffrey S., 1976. Population projections utilizing age-specific and age-parityspecific birth rates predicted with time series models: Projections with confidence limits. Unpublished Ph.D dissertation, Department of Social Relations, The Johns Hopkins University, Baltimore.
- Saboia, Joao L. M., 1974. Modeling and forecasting populations with time series: The Swedish case. Demography 11 (3, August): 483-492.
- Schweder, Tore, 1971. The precision of population projections studied by multiple precision methods. Demography 8(4, November):441-450

Sykes, Zenas M., 1969. Some stochastic versions of the matrix model for population dynamics. Journal of the American Statistical Association 64 (March):111-130.

- Whelpton, Pascal K. and Arthur A. Campbell, 1960.
 Fertility Tables for Birth Cohorts of American
 Women. Part I. Annual and Cumulative Birth
 Rates, by Age, by Order of Birth for All Women
 in Cohorts of 1876 to 1943. Vital Statistics
 Special Reports. Selected Studies 51 (1,
 January 29). United States Public Health
 Service, Washington, D. C.: Government
 Printing Office.
- Zellner, Arnold, 1975. Time series analysis and econometric model construction. Pp. 373-398 in R. P. Gupta (editor), Applied Statistics. Chicago: North-Holland Publishing Company.

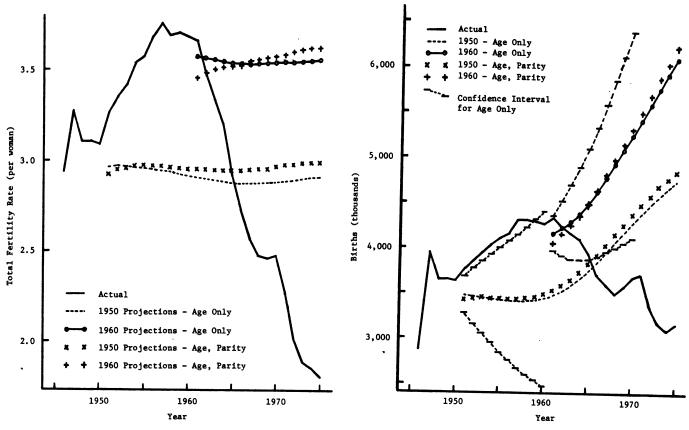
TABLE 1

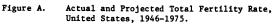
"Best"	Fitting ARIMA Models for Time Series of Age-Specific	
	Birth Rates for Women Aged 14-49, 1917-1971	

Age	Model (p,d,q)	Q-Value	Probability ¹	Residual Variance	Mean	Autoregressive Coefficient Lag 1 Lag 2		Moving Average Coefficient Lag 1 Lag 2	
14	210	10.2	0.99	0.15	3.86	-0.359	-0.203		
15	110	14.6	0.93	0.80	10.66	-0.010			
16	210	9.5	0.99	4.58	29.30	0.205	-0.170		
17	110	13.1	0.96	19.08	59.02	0.125			
18	210	18.3	0.74	49.11	99.41	0.189	-0.174		
19	210	18.9	0.71	91.34	137.54	0.234	-0.127		
20	110	19.0	0.75	120.66	159.54	0.196			
21	110	14.5	0.94	140.68	172.34	0.218			
22	110	17.0	0.85	149.49	180.51	0.191			
23	111	23.2	0.45	131.96	185.52	-0.272		-0.613	
24	110	23.0	0.52	148.33	183.64	0.152			
25	111	16.9	0.81	67.72	170.42	-0.177		-0.615	
26	210	26.6	0.28	73.27	162.42	0.317	-0.250		
27	111	16.4	0.84	54.45	151.10	-0.300		-0.741	
28	210	22.7	0.48	39.57	146.39	0.471	-0.170		
29	110	18.1	0.80	37.43	131.62	0.268			
30	220	27.3	0.24	21.63	123.89	-0.351	-0.560		
31	111	18.1	0.75	17.60	101.92	0.891		0.658	
32	111	13.1	0.95	16.64	100.65	0.897		0.634	
33	210	21.9	0.53	12.88	88.63	0.424	0.127		
34	111	15.5	. 0.88	13.78	80.86	0.895		0.665	
35	112	10.8	0.98	7.67	74.49	0.886		0.414	0.108
36	111	10.3	0.99	6.29	65.97	0.900		0.554	
37	220	20.8	0.59	5.85	56.14	-0.763	-0.365		
38	211	10.8	0.98	3.63	53.65	0.573	0.345	0.423	
39	220	10.5	0.99	3.28	41.77	-0.854	-0.416		
40	111	17.9	0.76	1.32	33.98	0.965		0.639	
41	211	13.2	0.93	0.72	21.90	0.777	0.184	0.644	
42	220	17.8	0.77	0.97	18.85	-0.909	-0.345		
43	221	17.8	0.72	0.27	12.02	-0.603	-0.507	0.137	
44	121	13.2	0.95	0.21	7.17	-0.317		0.824	:
45	121	14.8	0.90	0.08	4.89	-0.105		0.660	
46	211	15.3	0.85	0.03	2.32	0.400	0.572	0.686	
47	210	16.7	0.82	0.02	0.98	-0.041	0.285		
48	111	8.3	0.99+	0.01	0.48	0.185		-0.130	
49	121	15.7	0.87	0.01	0.34	-0.496		0.863	

¹ Degrees of freedom = 25-p-q

² Births per 1,000 women





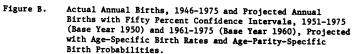


TABLE 2

Total Population, Births, Confidence Intervals, and Annual Rates of Change -- Projections from Base Year 1950 Using Age-Specific Birth Rates: 1950 to 1975 (Populations in thousands Based on Year of April 1 - March 31)

Year	Population ¹	507 Confidence Interval	Births	50% Confidence Interval	Total Fertility Rate ²	Crude Birth Rate ³	Crude Death Rate ³	Percent Natural Increase
1950	150,216	(X)	(X)	(X)	(X)	(X)	(X)	(X)
1951	152,739	±199	3,481	±192	2,968	22.8	9.5	1.33
1952	155,230	839	3,471	305	2,970	22.4	9.5	1.29
1953	157,688	1,484	3,458	403	2,970	21.9	9.4	1.25
1954	160,110	2,274	3,443	492	2,966	21.5	9.4	1.21
1955	162,499	3,203	3,430	578	2,962	21.1	9.4	1.17
1956	164,857	4,260	3,420	657	2,957	20.8	9.4	1.14
1957	167,190	5,455	3,415	740	2,949	20.4	9.4	1.10
1958	169,507	6,350	3,418	814	2,940	20.2	9.4	1.08
1959	171,815	7,755	3,430	890	2,931	20.0	9.3	1.07
1960	174,124	9,285	3,453	965	2,922	19.8	9.3	1.05
1961	176,446	(X)	3,487	(X)	2,912	19.8	9.3	1.05
1962	178,836	(X)	3,535	(X)	2,906	19.8	9.1	1.07
1963	181,224	(X)	3,593	(X)	2,898	19.8	9.3	1.05
1964	183,629	(X)	3,664	(X)	2,889	20.0	9.5	1.05
1965	186,130	(X)	3,748	(X)	2,881	20.1	9.3	1.08
1966	188,692	(X)	3,849	(X)	2,878	20.4	9.4	1.10
1967	191,320	(X)	3,957	(X)	2,879	20.7	9.5	1.12
1968	194,063	(I)	4,069	(X)	2,684	21.0	9.3	1.17
1969	196,834	(X)	4,177	(X)	2,886	21.2	9.6	1.16
1970	199,716	(X)	4,284	(X)	2,888	21.5	9.4	1.21
1971	202,722	(I)	4,391	(X)	2,893	21.7	9.2	1.25
1972	205,843	(X)	4,496	(X)	2,899	21.8	9.0	1.28
1973	209,023	(X)	4,590	(X)	2,903	22.0	9.0	1.30
1974	212,253	(I)	4,676	(X)	2,910	22.0	9.1	1.29
1975	215,527	(I)	4,751	(X)	2,914	22.1	9.1	1.30

(X) Not available or not applicable

¹ April 1 population

² Per 1,000 women

³ Per 1,000 mid-year population