

APPLICATIONS OF POPREP, A MODIFICATION OF POPSIM

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## 1. Introduction

POPSIM is a stochastic micro-simulation model which can be used to study either cohort or period populations. It was described at the 1969 IUSSP meetings, and in more detailed form in a series of working papers (1,2). It is a two-sex model which allows for feedback mechanisms. In POPSIM, births are generated by using the probability of a live birth rather than generating a sequence of biological events such as conception, possible fetal loss, or sterility.

This paper will describe some modifications to POPSIM that incorporate these biological factors. We have retitled this version POPREP, but the major part of the model is identical to POPSIM. We also describe some studies that are in progress using POPREP.

## 2. Background (POPSIM)

Although there are two versions of POPSIM available, we describe here only the "open" model which is used as the basis for POPREP.

"The initial population can be thought of as a random sample of individuals selected from a population register, but without regard to familial relationships. Thus, a married female may be selected for the computer population, but her husband may not be chosen. Since marriage partners and offspring are not necessarily included when the sample is selected, the information concerning these individuals is carried in the computer records of the sample individuals. Just as the sample individuals constitute a valid sample of the population register, so also the simulated computer population at a future date is a random sample of individuals from a similar population register at the corresponding date.

POPSIM creates initial populations in the computer by means of a series of subroutines which use random sampling of inverse probability distribution functions, for the most part, to assign a consistent set of characteristics to each individual. ...For convenience of programming and processing, each record also indicates the next event and the date of next event. A stratified random sampling procedure is used to assign ages." (2)

In POPSIM, the generation of the initial population is done by means of a separate computer program, but in POPREP, the initialization and

vital event generation are performed in one program. To insure consistency for each individual alive at the start of simulation, we generate a history conditional on survival to that time. For example, if our initialization specifies that we have a 30 year old woman, we generate a history of marriages, births, divorces and widowhoods up to age 30, using the appropriate event probabilities.

"[POPSIM] generates marriages, births, divorces and deaths for individuals using stored matrices of monthly transition (event) probabilities. A conditional probability approach is used which permits these event probabilities to depend on the current characteristics and prior history of the individual.

An event-sequenced simulation procedure is used in which an individual is processed only when an event occurs to him. The first step in this procedure is to generate the date of the next vital event for each individual in the initial population. Since the type of event to occur next (i.e., a birth or a change in marital status or a death) is not known, a date for each of the eligible events for the individual is generated and the event with the earliest generated date is chosen as the next event for that individual. Only this next event and its date are carried in the record for each individual. This procedure for generating the next event is accurate under the assumption that the input parameters are independent probabilities for the competing events (or net rates) rather than crude rates." ( 2 )

To calculate the date of the next event, a hazard function technique is used. Thus, the conditional probability of an event occurring given that no event has yet occurred is assumed, say  $\mu(t)$ . It is known that  $\mu(t)=f(t)/(1-F(t))$  where  $f(t)$  is the unconditional density function of this particular event and  $F(t)=\int_0^t f(y)dy$ . Usually the value of  $\mu(t)$  has been assumed to be piecewise linear.

"The second step in the event-sequenced simulation procedure is to process each individual on the date of their next event. Processing consists of recording the essential facts concerning the event, changing the status of individual characteristics affected by the event, and then generating the date of the next event for the individual.

The computer program which generates vital events also provides tabulations of the initial population and of subsequent populations at the end of specified intervals of simulated time. These tabulations include the distribution of the computer population by age, sex and marital status and counts of the births, deaths, marriages and divorces that occurred during the time

interval by various characteristics of the individual at the time of the event.

POPSIM [also] permits a vital event history tape to be written for each individual in the computer population. The data on this tape are equivalent to data collected from a sample of individuals in a longitudinal survey. Separate tabulation programs have been written for the history tape." ( 2 )

This program does not lend itself easily to experiments on contraception and abortion. For example, it has been shown ( 5 ) that if women use a contraceptive with an effectiveness of 0.9, their birth rate is expected to be reduced by less than 0.9, because fecundability (which is reduced by contraceptives) is only one of the factors that affects birth rates (a contraceptive that is 0.9 effective reduces the fecundability to 10% of its natural value). Other important factors are the duration of pregnancy, the duration of the postpartum anovular (nonsusceptible) period and the proportion of pregnancies that end in spontaneous or induced fetal losses. The effect of a contraceptive (when used) depends on the distributions governing these functions.

Furthermore, the main feature of modern contraceptives such as the intrauterine devices (IUD) or hormones, is that they have fairly high discontinuation rates which vary with the woman's age and parity. It is awkward to provide for this eventuality in calculating birth probabilities.

Experience with a biological model, REPSIM, had shown that a more direct and satisfactory approach to these problems is provided by considering the biological functions in the model ( 4 ). For these reasons, the birth routines in POPSIM were modified as described below.

### 3. POPREP, The Biological Version of POPSIM

POPSIM was modified by eliminating the birth subroutines and replacing them by a set of subroutines dealing with conception, fetal loss, induced abortion and live birth. One of the simplifications obtained was the elimination of special treatment of live births following widowhood or divorce.

The conception routines contain six parts:

1. Determination of age at menarche
2. Determination of age at sterility
3. Determination of maximum fecundability
4. Calculation of the date of next conception
5. Determination of the outcome of the pregnancy
6. Determination of the length of post-partum infecundability

Parts 1, 2, and 3 set parameters dealing with each woman and are determined once during initialization.

The age at menarche is chosen from a normal distribution with mean 13.2 and standard deviation 1. This fits the U.S. data fairly well. However, these parameters may be easily modified for other populations.

The age at sterility,  $S$ , is chosen from a distribution in which  $\ln(50-S)$  has a normal distribution with mean = 1.9 and standard deviation = 0.5. Thus, the mean age at sterility is 42.4 with standard deviation 4. This too is modifiable at the user's option. If the age at sterility is less than the age at menarche, it is assumed that the woman never becomes fecund.

The maximum fecundability is chosen from a discrete distribution that is approximately Beta. It is given in Exhibit 1, below. Its mean is approximately .2 and its harmonic mean .13. We originally planned to sample directly from the Beta distribution, but chose this distribution for simplicity of programming and speed of execution.

Exhibit 1  
Distribution of Maximum Fecundability

<u>Fecundability Level</u>	<u>Probability</u>
.05	.1428
.10	.1700
.15	.1721
.20	.1506
.25	.1253
.30	.0839
.35	.0620
.40	.0933

The pattern of fecundability for each woman by age has a trapezoidal shape. It is zero before age at menarche and after the age at sterility. Denote the length of the fecund period by  $L = (\text{Age at sterility}) - (\text{Age at menarche})$ . The fecundability of a woman rises linearly from 0 at age at menarche to its maximum level at  $L/6$ , remains at that level until  $L/2$ , and declines linearly to 0 at age of sterility. The fecundability function  $\mu(t)$  is sketched in Exhibit 2.

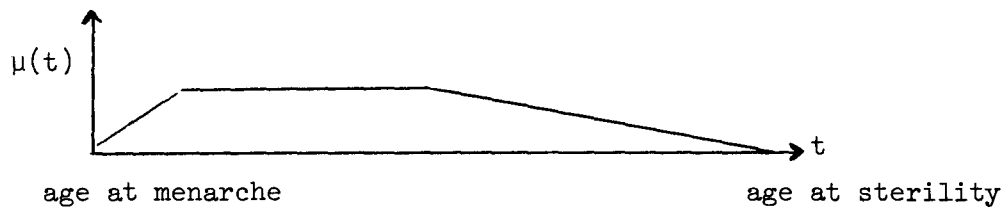


Exhibit 2  
Shape of Fecundability Function

The date of next conception is calculated by obtaining a random number  $R$  and solving the equation

$$R = 1 - \exp\left(-\int_{t_0}^{t_c} \mu(t) dt\right),$$

for  $t_c$ , where  $t_0$  is the age at the time of the last event. If  $t_c$  is the earliest of all competing events, then the next event is a conception.

When conception is the next event, the outcome of the pregnancy must be determined. The possible "natural" outcomes are live birth or spontaneous abortion. When induced abortion is introduced, this also is an outcome of a pregnancy. The probability that a pregnancy ends in a spontaneous abortion is a function of the female's age

$$PFL = .000833 \text{ age}^2 - .0433 \text{ age} + .7625$$

where age is measured in years. This function has the value 0.23 at age 20, 0.20 at age 25 and 0.50 at age 45. A uniform (0,1) random number is compared with the probability of spontaneous abortion for the appropriate age of the woman. If the random number is less than this value, the woman has a fetal loss. In this case, the length of the pregnancy  $Q$  has an exponential distribution truncated at 9 months.

$$f(Q) = \lambda \exp(-\lambda Q) / (1 - \exp(-9\lambda))$$

We have assumed  $\lambda = .5$  which gives  $Q$  a mean of 1.9 months and a variance of 3.08 months. A more realistic model might have been a mixture of exponentials to account for early and late fetal loss, but this was felt to be more complicated than we desired. If the pregnancy ends in a live birth, the length is assumed to be 9 months.

The probability of induced abortion conditional on no spontaneous abortion occurring first is  $1 - PLB$ , where  $PLB$  is an input function of parity. If an induced abortion occurs, the length of the pregnancy has a exponential

distribution truncated at 5 months with the form:

$$f(t) = \frac{-5}{\ln PLB} \exp\left(\frac{\ln PLB}{5} t\right) / (1 - PLB)$$

This length of pregnancy is compared with that generated for the natural outcome to determine what actually occurs. A separate value of PLB is input for each of parities 0, 1, 2, 3, 4, and 5+.

Post-partum anovulation lasts 2 months after a (natural or induced) fetal loss and follows an exponential distribution with a mean of 5 months after a live birth. If the child dies, the post-partum anovulation period cannot continue more than one month after the death.

Contraception is implemented in POPREP in two parts. If a woman is using contraceptive  $i$  (which may be no contraceptive), her fecundability is multiplied by the complement of the use-effectiveness to obtain the effective fecundability. Thus for non-users, the multiplier is 1.0, while for a device that is 0.95 effective, the multiplier would be 0.05. The second part of the contraception routines relates to changing contraceptive methods. This is treated exactly as other events are: a time to contraceptive change is computed; if it is the earliest event, then the next event is a change in contraceptive method. At present, the hazard function being used, if there has been no contraception state change since the last pregnancy (or marriage) is

$$h(t) = \begin{cases} A_i & t < 12 \\ A_i (t/12)^{K-1} & t > 12, \end{cases}$$



for  $t$  = time (months) since last pregnancy and, if there has already been a contraceptive change:

$$h^*(t) = h(t+12)$$

for  $t$  = time since last change of state. In these functions,

$$A_i = C_i + D_i \cdot \text{Age (in Months)} + E_i \cdot \text{Parity},$$

and

$$0 < K < 1.$$

$K$ ,  $C_i$ ,  $D_i$  and  $E_i$  are determined by the user. The last three are specific for the  $i$ th contraceptive state. An option exists to set  $A_i = 0$  for some contraceptive state. If  $A_i \neq 0$ , this function appears as in Exhibit 3.

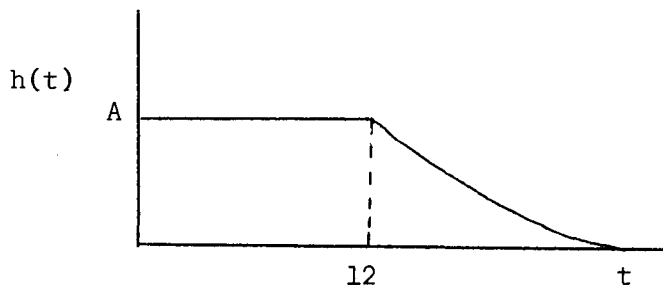


Exhibit 3  
Hazard Function for Contraceptive Change

If  $K=1$ , the function is a horizontal line with  $h(t)=A_i$ , and the resulting distribution is exponential. Some examples of the coefficients, multipliers, and the probabilities of change within 12 months for a 30 year old, parity 2

woman are given in Exhibit 4.

Exhibit 4

Coefficients for  $A_i$ , Fecundability Multipliers, and Probability of Change

i Type	$C_i$	$D_i$	$E_i$	P(Change in 12 months)	Fecundability Multipliers
1 None	.215	-.00051	.0166	.54	1.00
2 Conventional	.172	-.00029	-.0124	.40	0.25
3 Modern	.167	-.00029	-.0112	.38	0.05

If a contraceptive change is the next event, the new contraceptive state must be determined. A conditional transition matrix is used such that there are zeros on the main diagonal and the rows add to one. The matrix that has been used is given in Exhibit 5.

Exhibit 5

Conditional Transition Matrix

Initial State	Final State		
	1	2	3
1	0	.25	.75
2	.50	0	.50
3	.50	.50	0

The transition matrix may be specified by the user. It may depend on parity, in which case there is a matrix for each relevant parity. Or it may be based on a desired stationary distribution among the states, depending on age and parity. A cumulative distribution technique is used to find the final state.

At Conception, a woman is placed in the non-using state.

#### 4. Fertility Measures Based on Birth Interval Data

In recent years, various fertility rates have been used to study the births occurring to populations. They have been found unsuitable for rapid detection of changes in the reproductive performance of women. Some require large samples, some do not reflect changes rapidly, some pool groups of women whose performance is quite different. These considerations have led to the study of birth intervals as a potentially good measure for fertility. However, some drawbacks have been noted in literature; in particular, the truncation effect due to the limited length of time a woman has to complete her child-bearing has been studied by Sheps et al (6). Poole (3) has developed a set of estimators based on birth intervals that consider the truncated nature of the data.

Given that there is an  $(i-1)$ th birth, the function  $F_i(x)$  is defined as the probability (in the absence of competing risks) that there is an  $i$ th birth within  $x$  units of time (after the  $(i-1)$ th birth).  $F_i(x)$  is assumed to be independent of age.  $F_i(x|a)$  is the corresponding age-dependent probability that is conditional on an  $(i-1)$ th birth occurring at age  $a$ . The first birth is measured from the date of marriage, which may be called the  $0$ th birth. Note that the  $F_i$  are defective, in that, in general,  $F_i(\infty)$  or  $F_i(\infty|a)$  is not equal to one.

Following Sheps and Menken (7), Poole considered several schemes for ascertainment of the  $i$ th intervals to be measured, including prospective observations (which include data on all births occurring up to survey time, regardless of whether the women remain alive and married) and retrospective observations (which include data only on births occurring to "survivors", women

who are still alive and married at survey time). Poole developed life table estimators  $\hat{F}_i(x|a)$ , appropriate for these schemes, using data on closed (completed)  $i$ th intervals (from the  $(i-1)$ th birth to the  $i$ th birth), open intervals (from the  $(i-1)$ th birth to survey time, in cases where women remain eligible but have no  $i$ th birth before the survey), and exposure intervals ended by death, divorce, or widowhood (from the  $(i-1)$ th birth until the woman becomes "ineligible"). Note that data on the last type of interval is unavailable in a retrospective study, as defined above.

Consideration was also given to developing indices from combinations of the estimators. For example, letting  $w_i(a)$  be a suitable weighting factor for  $\hat{F}_i(x|a)$ , then

$$\hat{F}_i(x) = \frac{\sum_a w_i(a) \hat{F}_i(x|a)}{\sum_a w_i(a)}$$

and

$$\hat{B}(x) = \frac{\sum_a \sum_i w_i(a) \hat{F}_i(x|a)}{\sum_a \sum_i w_i(a)}$$

There is further work to be done in establishing suitable  $w_i$ .

## 5. Tests of Fertility Measures

Several limited tests of the life table estimators  $\hat{F}_i(x|a)$  have been made as follows:

- (a) In order to check the accuracy of the estimators, it was desired to make a comparison with the true (theoretical) distributions being estimated. Theoretical values could not easily be computed for birth intervals, so intervals between conceptions were considered instead (using estimators of the same form as for birth intervals). In two independent runs, life histories, including conceptions and births, were simulated for a cohort of 500 women having identical biological parameters, married at age 18, and using no contraception. Estimates  $\hat{F}_1(x|18)$  and  $\hat{F}_2(x|19)$  were determined from prospective data from surveys at age 24 (marital duration 6 years). These estimates were then compared with theoretical values  $F_1(x|18)$  and  $F_2(x|19)$ . (These distributions refer to conception rather than birth intervals.) Graphs of the true distributions and estimates appear in Exhibits 6 and 7. The estimates were close to the theoretical results.
  
- (b) From the same simulations,  $F_1(x|18)$  for the first birth interval was estimated from prospective data and from retrospective data from surveys at age 21. The retrospective estimates compared well with the prospective estimates, which were taken as a standard. Graphs of these estimates appear in Exhibit 8.
  
- (c) In order to test the value of the life table estimators for discriminating between different populations, two populations were simulated, be-

ginning with the same cross-sectional distribution of ages, one with and one without contraception and induced abortion. (The former had 2000 females initially and the latter had 1000.) An index  $\hat{B}(x)$  (combining the various estimates  $\hat{F}_i(x|a)$ ) was computed for each population using retrospective data from a survey 3 years into the simulation. (Note that data from more than 3 years history was available, since complete life histories were simulated for every individual alive at the beginning of the simulation.) The index  $\hat{B}(x)$  discriminated well between the two populations. Graphs of the two estimated distributions appear in Exhibit 9.

- (d) Finally, the effect of sample size has been tested. An initial population of 4000 females of various ages was simulated for 30 years, with no contraception or abortion. Life table estimates  $\hat{F}_i(x|a)$  for several  $i$ , a combinations were computed, first using all prospective data for the entire simulation (30 years plus previous experience of women alive at time zero), and then using prospective data beginning at the 25-year point. (Since the same population parameters were in effect throughout the simulation, the data from the 5-year period was considered a valid subsample of the complete data.) There was close agreement between the large-and small-sample estimates. Graphs of a typical pair of estimates are shown in Exhibit 10.

One of the most important questions still to be investigated is the behavior of the life table estimators under changing conditions, such as initiation of a contraceptive program.

In a separate experiment, various birth interval measures of fertility were studied to determine their robustness to reporting errors. Errors were introduced in the following way. Given a 30-year simulation of a population not using contraception or abortion (described in part (d) above), each woman's history was modified by adding a random normal deviate to all birth dates, subject to the condition that the order among the events: marriage, first birth, second birth, ..., and survey, was preserved. Note that the dates of marriage and survey were not changed. It was assumed that in practice, a religious or civil record of marriage date would be available, and so might be relatively accurately determined.

Three error models are considered here:

- (a)  $\mu=0$ ,  $\sigma=6$  months
- (b)  $\mu=12$  months,  $\sigma=6$  months (positive bias)
- (c)  $\mu=-12$  months,  $\sigma=6$  months (negative bias)

The unbiased case ( $\mu=0$ ) would arise from general uncertainty about dates, with no tendency to report dates earlier or later than the true ones. The positive bias case would arise if an interviewee reported all dates as occurring more recently than they actually did. The case of negative bias would arise when events were reported as occurring earlier than they actually did. Note that, in each model, the mean date adjustment is not actually the  $\mu$  specified, because of the truncation effect of preserving the order of events.

The fertility measures considered were:

- (a) the  $i$ th closed interval (the length of time the  $(i-1)$ th to the  $i$ th birth), for women of age  $a$  at survey time.
- (b) the open interval (from the last birth to the survey date), for women of age  $a$  and parity  $(i-1)$  at survey time.
- (c) the life table estimators (described above), for women of age  $a$  at parity  $(i-1)$ .

For the original, unmodified population history, and for two independent replicates of each of the three error models, all of these fertility measures were computed from retrospective data on all women who were alive and married at the 30-year point. The results of these experiments is summarized separately for each type of fertility measure.

Consider first the observed closed  $i$ th intervals. In the no-bias case ( $\mu=0, \sigma=6$ ), there was a slight additional variability because of the random perturbations of the dates. In general, the mean intervals were quite similar to the true values. When a positive bias is included ( $\mu=12, \sigma=6$ ), the first closed interval appears much longer than its true value, because the date of marriage is fixed, while the date of the first birth is increased by about 12 months, on the average. The last closed interval is shorter than the true value, in general. The next-to-last birth date tends to be increased by about 12 months, while the adjustment of the last birth date is limited, since it must precede the survey date, which is fixed. The intervals other than the first and last remain very close to their true values, since the  $(i-1)$ th and the  $i$ th birth dates tend to be adjusted by about the same amount. If a negative bias is included ( $\mu=-12, \sigma=6$ ), the first interval is shortened by the same process accounting for the behavior of that interval in the positive bias case. All other closed intervals, including the last one, are unaffected except for increased variance. See Exhibit 11 for a table of some of the closed interval data.

The behavior of the open interval under reporting errors is affected by the same processes as the closed intervals. For the unbiased perturbation case, there is increased variability, but no observable trends. Generally the perturbed dates give mean intervals that are within one month of the true value.



If positive bias holds, the open interval is decreased noticeably, as would be expected, since the last birth date tends to be increased while the survey date remains fixed. Similarly, the open interval increases, on the average, for the negative bias case. Open interval data is tabulated in Exhibit 12.

The life table estimators of birth interval distributions are based in large part on closed intervals, so their behavior is not unlike that of the closed intervals. For unbiased perturbations, the estimates of the cumulative distribution is very close to those from the true data. For positive bias, the life table estimator for the first interval is stochastically greater than when there is accurate reporting. That is, there is a tendency for longer intervals to be estimated than in the unperturbed case. For other intervals, the estimated distributions are quite close. For the negative bias case, the distribution estimate for the first interval is stochastically smaller than the estimate from accurate data. Estimates for all other intervals are unchanged except for increased variance. An example of the distributions estimated is shown in Exhibits 13 and 14.

Further studies of robustness should include different forms of reporting errors. A more realistic model of inaccuracies might have  $\mu$  and  $\sigma$  as functions of the difference between survey date and event date. Another problem that could be considered is omission of births, possibly depending on whether the child has died. This was considered elsewhere in a pilot study and will be further investigated in the future.

Exhibit 6

THEORETICAL AND LIFE TABLE ESTIMATES  
OF FIRST INTERCONCEPTION INTERVAL  
FOR WOMEN OF AGE 18 AT MARRIAGE  
(From Poole(3))

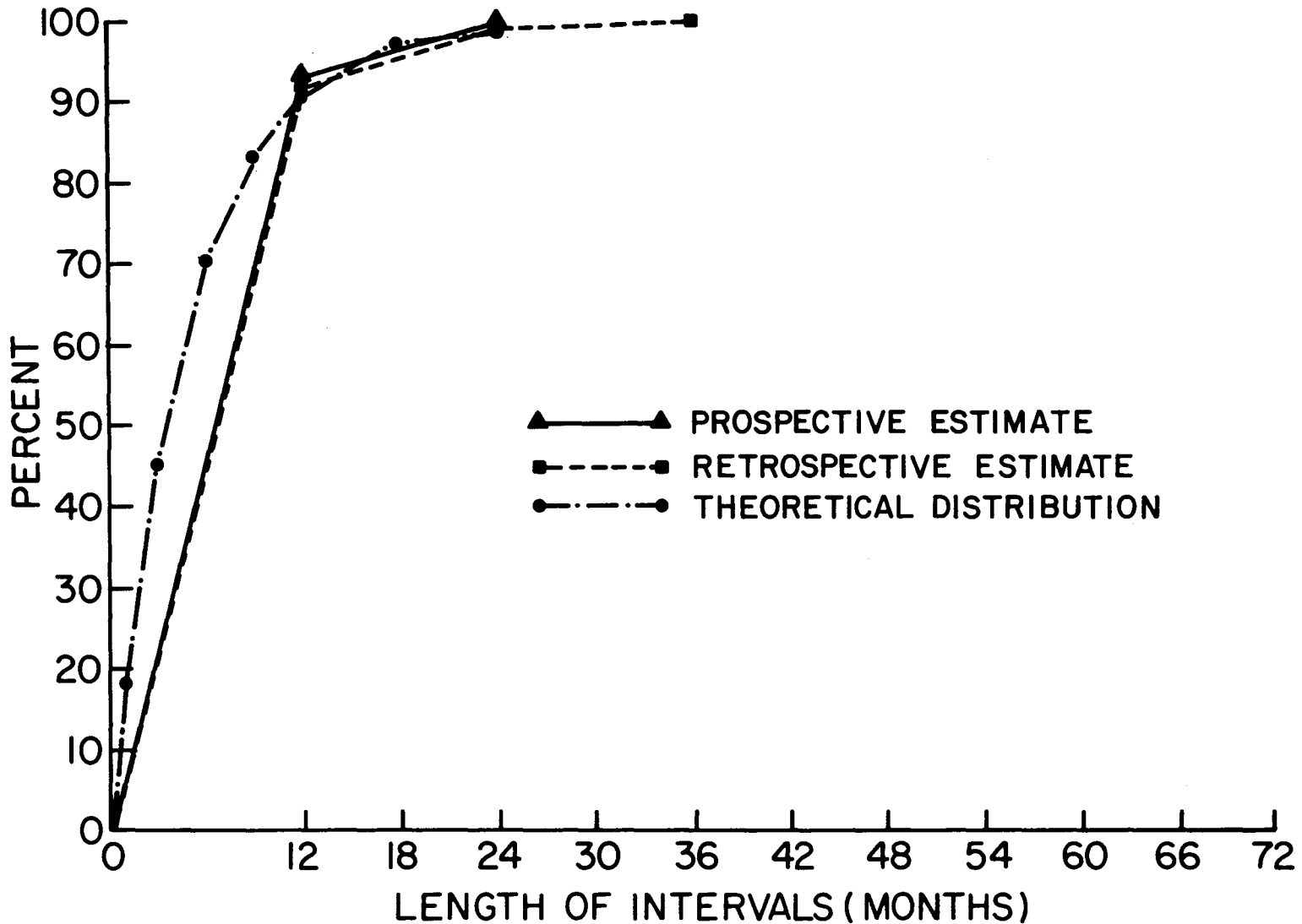


Exhibit 7

LIFE TABLE ESTIMATES OF SECOND INTERCONCEPTION INTERVAL  
FOR WOMEN OF AGE 19 AT FIRST CONCEPTION  
( From Poole(3) )

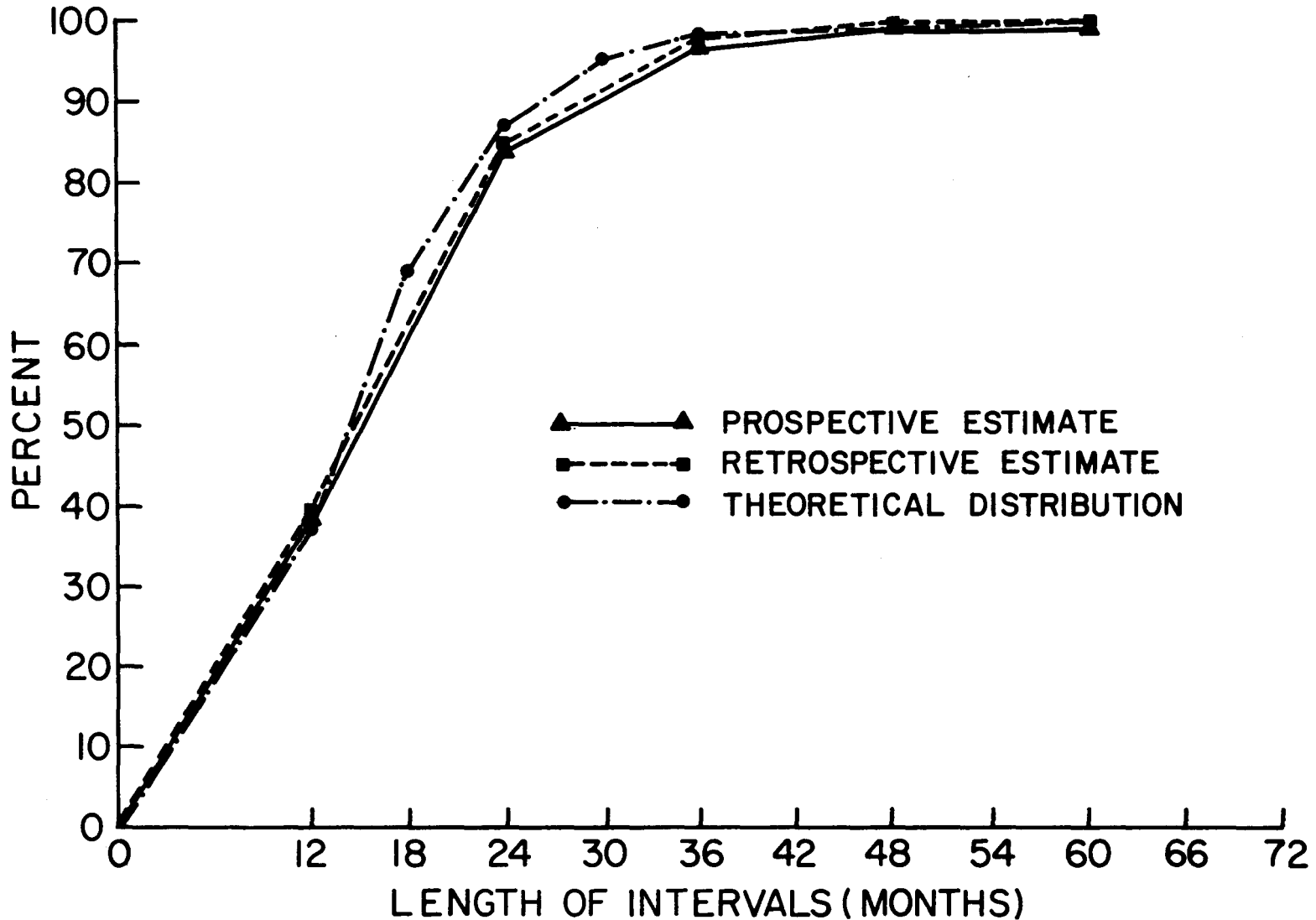


Exhibit 8

LIFE TABLE ESTIMATES OF FIRST BIRTH INTERVAL FOR WOMEN OF  
AGE 18 AT MARRIAGE

(From Poole(3))

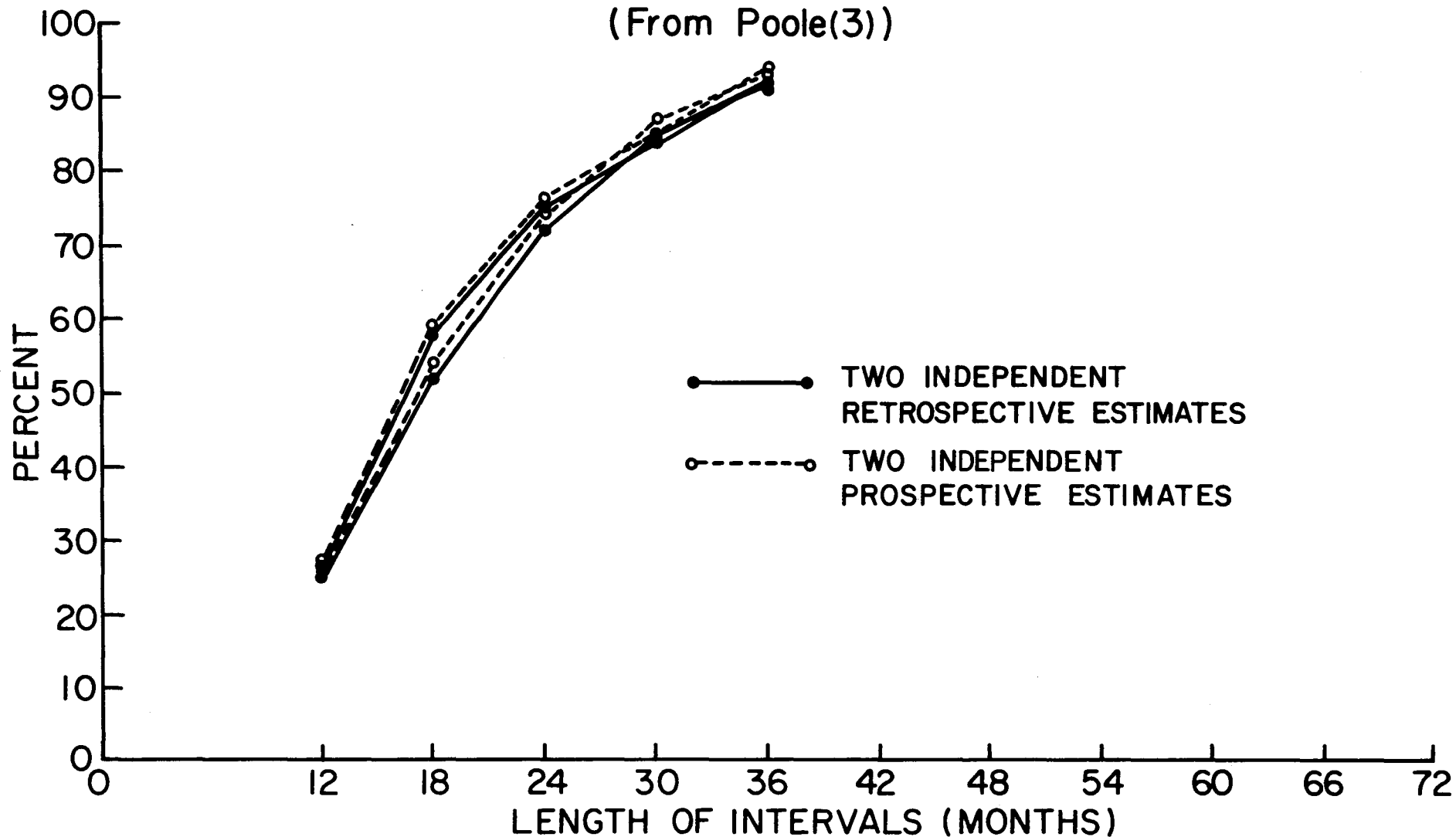
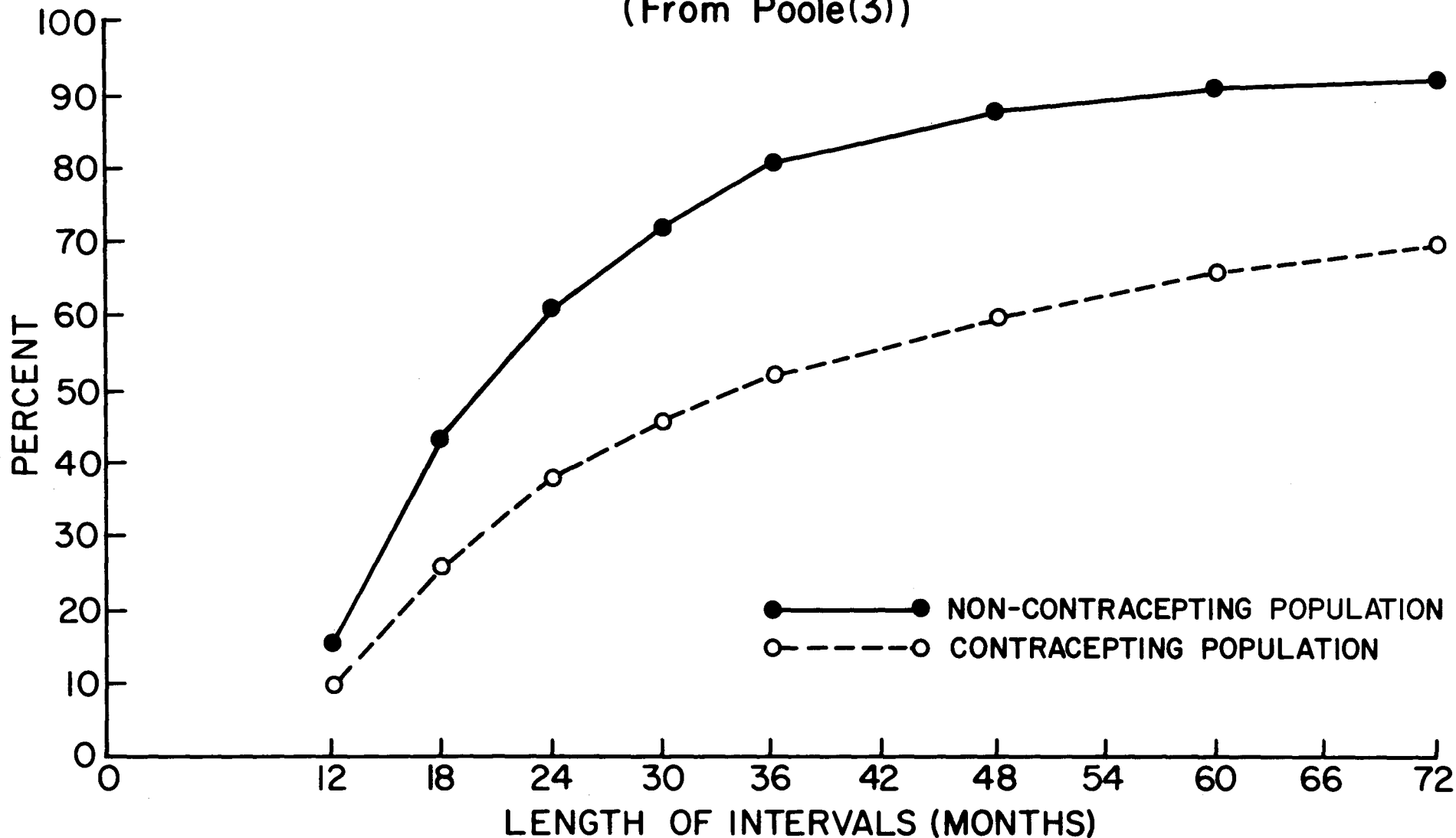


Exhibit 9

COMBINED LIFE TABLE ESTIMATES OF BIRTH INTERVALS  
FOR CONTRACEPTING AND NON-CONTRACEPTING POPULATIONS  
(From Poole(3))



**Exhibit 10**

**LIFE TABLE ESTIMATES OF SECOND BIRTH INTERVAL FOR WOMEN OF AGE 20-24 AT FIRST BIRTH**

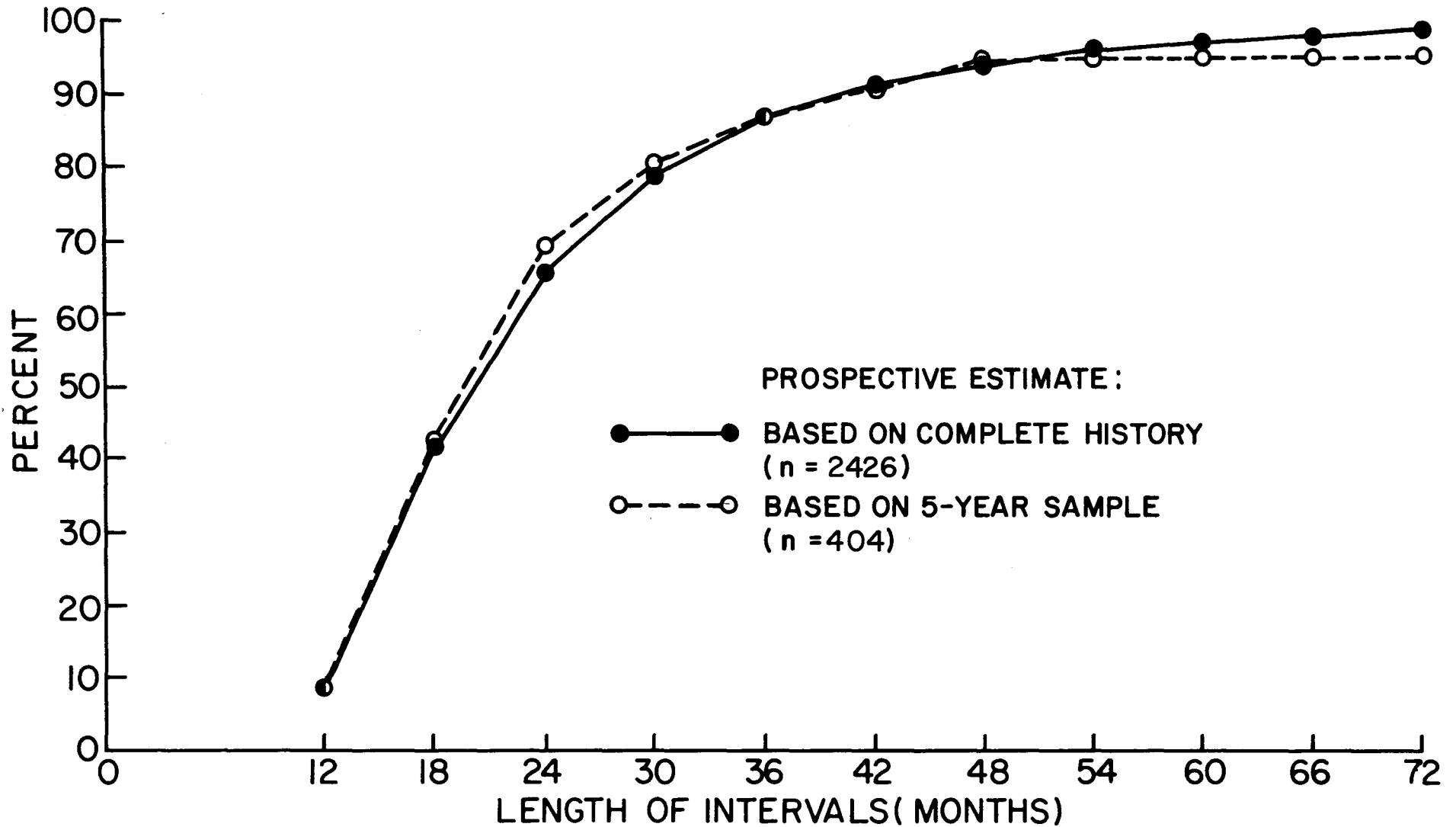


Exhibit 11

Closed Birth Intervals for Women of Age 20-24 at Survey

Parity	Number of Women	Interval Order			
		1	2	3	4
1	169	x =18.65 s =12.65 x <sub>1</sub> =17.75 s <sub>1</sub> = 0.15 x <sub>2</sub> =25.42 s <sub>2</sub> = 0.48 x <sub>3</sub> =10.00 s <sub>3</sub> = 0.28			
2	143	x =17.97 s =10.58 x <sub>1</sub> =18.47 s <sub>1</sub> = 1.07 x <sub>2</sub> =28.92 s <sub>2</sub> = 0.06 x <sub>3</sub> = 9.16 s <sub>3</sub> = 0.54	x =21.10 s =8.59 x <sub>1</sub> =19.33 s <sub>1</sub> =1.10 x <sub>2</sub> =16.19 s <sub>2</sub> =0.49 x <sub>3</sub> =18.20 s <sub>3</sub> =0.39		
3	89	x =17.09 s = 7.22 x <sub>1</sub> =17.59 s <sub>1</sub> = 0.67 x <sub>2</sub> =28.32 s <sub>2</sub> = 0.06 x <sub>3</sub> = 7.85 s <sub>3</sub> = 0.04	x =18.98 s =8.80 x <sub>1</sub> =19.08 s <sub>1</sub> =1.20 x <sub>2</sub> =19.51 s <sub>2</sub> =0.48 x <sub>3</sub> =17.36 s <sub>3</sub> =0.23	x =18.31 s =6.49 x <sub>1</sub> =16.65 s <sub>1</sub> =0.15 x <sub>2</sub> =12.72 s <sub>2</sub> =0.89 x <sub>3</sub> =17.55 s <sub>3</sub> =0.26	
4	36	x =14.54 s = 4.78 x <sub>1</sub> =14.63 s <sub>1</sub> = 0.12 x <sub>2</sub> =26.79 s <sub>2</sub> = 1.97 x <sub>3</sub> = 6.58 s <sub>3</sub> = 0.47	x =20.24 s =6.42 x <sub>1</sub> =18.99 s <sub>1</sub> =1.17 x <sub>2</sub> =21.17 s <sub>2</sub> =3.37 x <sub>3</sub> =16.72 s <sub>3</sub> =1.43	x =17.40 s =7.79 x <sub>1</sub> =19.09 s <sub>1</sub> =0.21 x <sub>2</sub> =15.52 s <sub>2</sub> =1.06 x <sub>3</sub> =17.61 s <sub>3</sub> =0.95	x =18.00 s =6.73 x <sub>1</sub> =16.25 s <sub>1</sub> =2.00 x <sub>2</sub> =11.45 s <sub>2</sub> =0.56 x <sub>3</sub> =18.41 s <sub>3</sub> =1.54

KEY

- x = Mean interval from unperturbed data
- x<sub>1</sub> = Combined mean interval from two replicates of  $\mu=0$  model
- x<sub>2</sub> = Combined mean interval from two replicates of  $\mu=12$  model
- x<sub>3</sub> = Combined mean interval from two replicates of  $\mu=-12$  model
- s = Standard deviation of intervals from unperturbed data
- s<sub>1</sub> = Between sample s.d. of  $\mu=0$  model
- s<sub>2</sub> = Between sample s.d. of  $\mu=12$  model
- s<sub>3</sub> = Between sample s.d. of  $\mu=-12$  model

All intervals measurements are in months.

Exhibit 12

Open Birth Intervals for Women of Age 20-24 at Survey

Parity	Number of Women	x	s
0	131	x =16.22 x <sub>1</sub> =16.22 x <sub>2</sub> =16.22 x <sub>3</sub> =16.22	s =16.15 s <sub>1</sub> = 0.00 s <sub>2</sub> = 0.00 s <sub>3</sub> = 0.00
1	169	x =13.80 x <sub>1</sub> =14.69 x <sub>2</sub> = 7.03 x <sub>3</sub> =22.44	s = 9.34 s <sub>1</sub> = 0.15 s <sub>2</sub> = 0.48 s <sub>3</sub> = 0.28
2	143	x =12.17 x <sub>1</sub> =13.42 x <sub>2</sub> = 6.12 x <sub>3</sub> =23.87	s = 9.70 s <sub>1</sub> = 0.02 s <sub>2</sub> = 0.54 s <sub>3</sub> = 0.15
3	89	x =11.26 x <sub>1</sub> =12.31 x <sub>2</sub> = 5.10 x <sub>3</sub> =22.87	s = 8.74 s <sub>1</sub> = 0.69 s <sub>2</sub> = 0.45 s <sub>3</sub> = 0.01
4	36	x = 8.08 x <sub>1</sub> = 9.28 x <sub>2</sub> = 3.32 x <sub>3</sub> =18.93	s = 6.57 s <sub>1</sub> = 1.17 s <sub>2</sub> = 0.90 s <sub>3</sub> = 0.40

KEY

- x = Mean interval from unperturbed data
- x<sub>1</sub> = Combined mean interval from two replicates of  $\mu=0$  model
- x<sub>2</sub> = Combined mean interval from two replicates of  $\mu=12$  model
- x<sub>3</sub> = Combined mean interval from two replicates of  $\mu=-12$  model
- s = Standard deviation of intervals from unperturbed data
- s<sub>1</sub> = Between sample s.d. of  $\mu=0$  model
- s<sub>2</sub> = Between sample s.d. of  $\mu=12$  model
- s<sub>3</sub> = Between sample s.d. of  $\mu=-12$  model

All intervals measurements are in months.



### Exhibit 13

## LIFE TABLE ESTIMATES OF FIRST BIRTH INTERVAL FOR WOMEN OF AGE 20-24 AT MARRIAGE

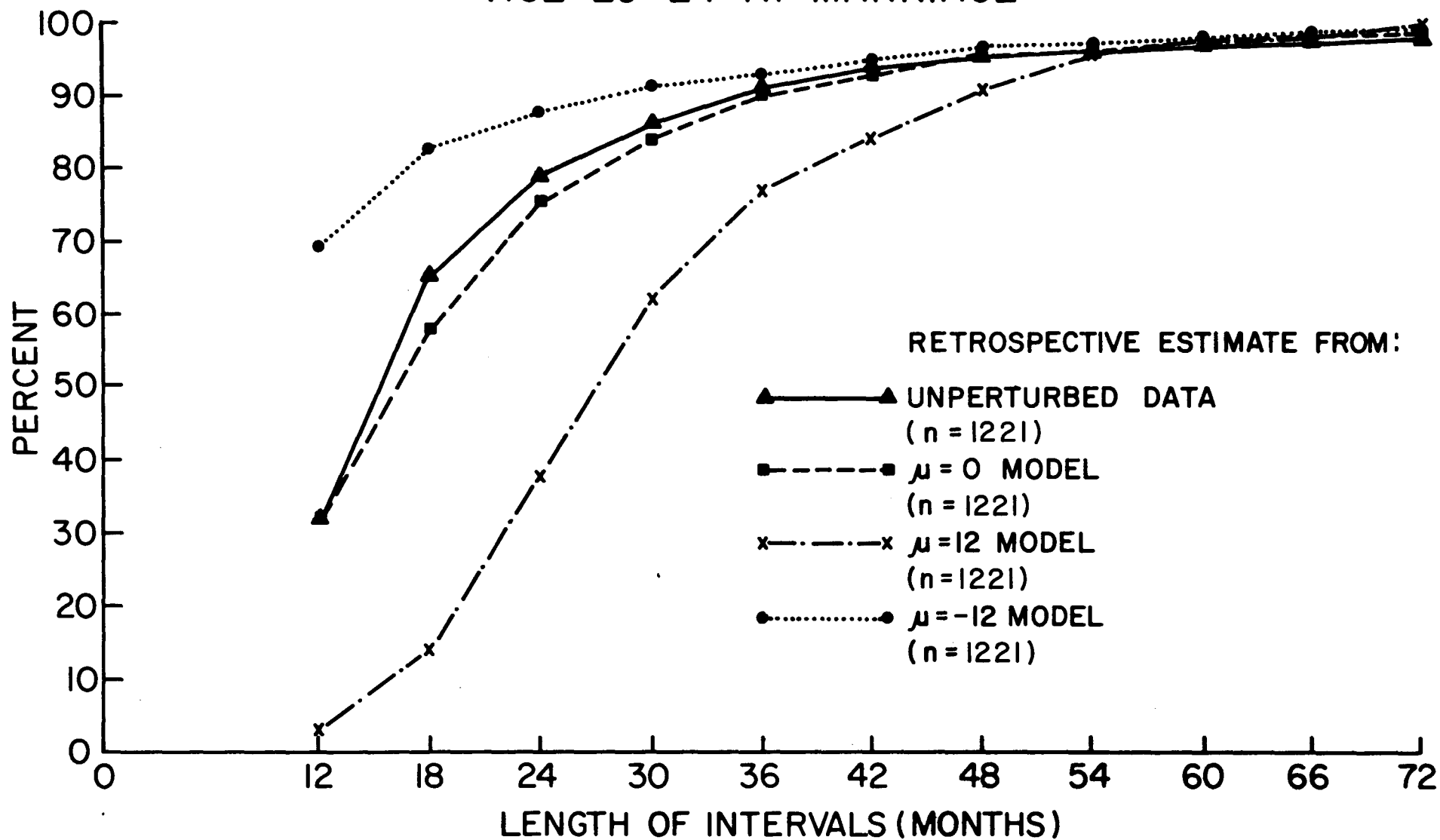
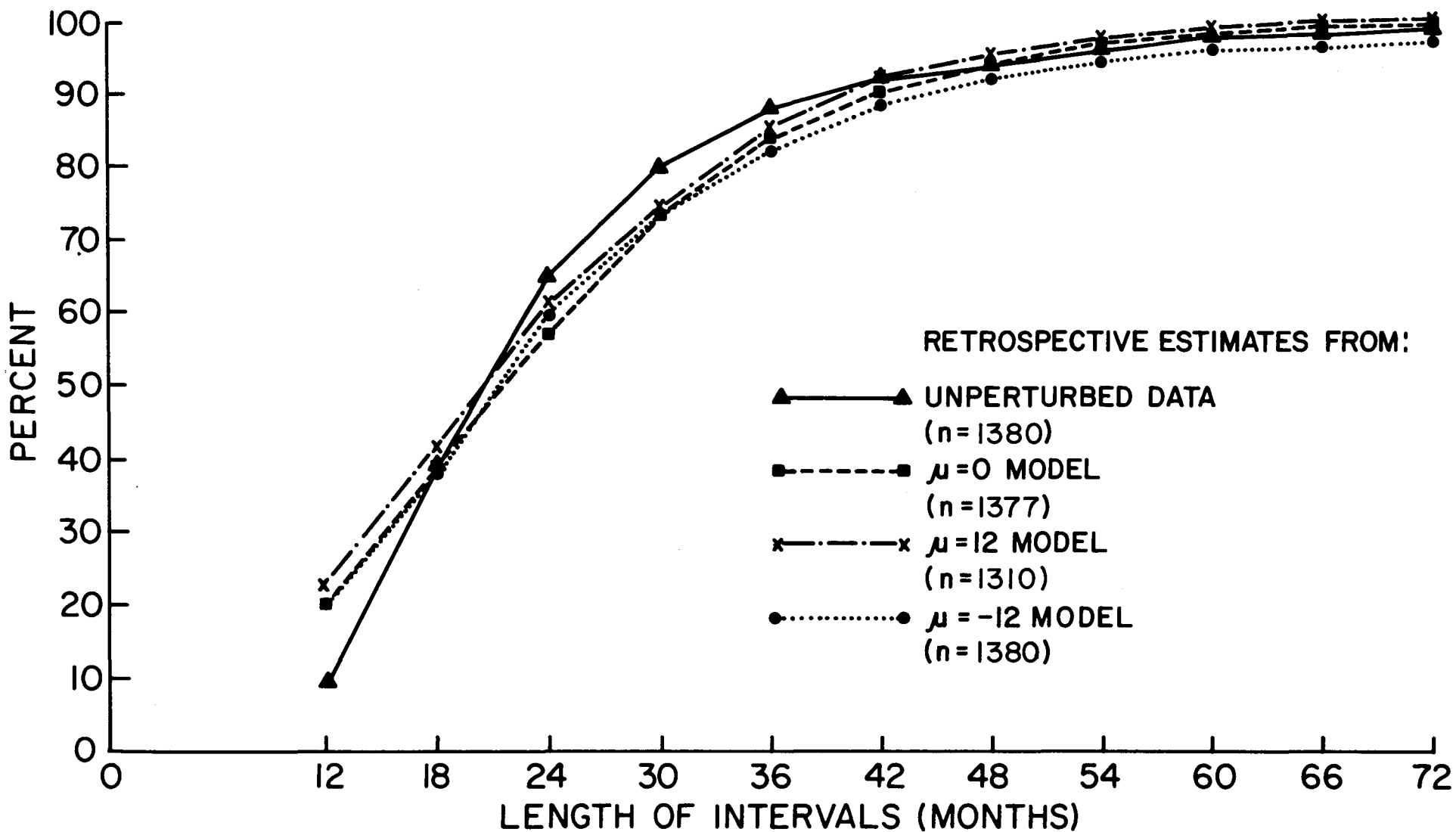


Exhibit 14

LIFE TABLE ESTIMATES OF THIRD BIRTH INTERVAL FOR WOMEN OF AGE 20-24 AT SECOND BIRTH



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