

# National Longitudinal Surveys

U.S. Department of Labor Bureau of Labor Statistics

Discussion Paper



The National Longitudinal Surveys (NLS) program supports many studies designed to increase understanding of the labor market and methods of data collection. The *Discussion Papers* series incorporates some of the research coming out of the program. Many of the papers in this series have been delivered as final reports commissioned as part of an extramural grant program, under which grants are awarded through a competitive process. The series is intended to circulate the findings to interested readers within and outside the Bureau of Labor Statistics.

Persons interested in obtaining a copy of any *Discussion Paper*, other NLS reports, or general information about the NLS program and surveys should contact the Bureau of Labor Statistics, Office of Economic Research, Washington, DC 20212-0001 (202-606-7405).

Material in this publication is in the public domain and, with appropriate credit, may be reproduced without permission.

Opinions and conclusions expressed in this document are those of the author(s) and do not necessarily represent an official position of the Bureau of Labor Statistics or the U.S. Department of Labor.



## NLS Discussion Papers

Responses of Female Labor Supply and Fertility to the Demographic Cycle

> Evangelos M. Falaris H. Elizabeth Peters

> > December1989

Report: NLS 92-9

### Responses of Female Labor Supply and Fertility to the Demographic Cycle

Evangelos M. Falaris University of Delaware

H. Elizabeth Peters University of Colorado

December 1989

This project was funded by the U.S. Department of Labor, Bureau of Labor Statistics under grant number E-9-J-8-0091. The research has also been supported, in part, by grants from the University of Delaware Research Foundation and from the University of Colorado Council on Research and Creative Work. Opinions stated in this paper do not necessarily represent the official position or policy of the U.S. Department of Labor.

#### Executive Summary

Objectives: We establish and measure the relation between the demographic cycle (or baby boom and baby bust), the timing of U.S. womens' first births and the timing of their return to work following the first birth.

Methodology: We propose a model according to which women alter the timing of the first birth and the return to work following that birth in order to mitigate any adverse effects of the demographic cycle on their wage profiles. The demographic cycle confronts women with different wage profiles depending on when they enter the labor market. Consequently, women would have an incentive to alter the timing of fertility and return to work so as to face a more advantageous wage profile than would otherwise be the case. We test the predictions of our model using data from three cohorts of the National Longitudinal Surveys of Labor Market Experience. The data include information for women born during different phases of the demographic cycle: 1918-37, 1942-53, 1957-64. We estimate hazard rate models which permit us to utilize information on women who have not had a first birth or have not returned to work by the latest observation period along with information on women who have experienced these events during the observation period. We also control for unobserved differences among women which may influence the timing of their first birth and return to work. We measure the effect of the demographic cycle by means of two relative birth cohort size variables. We also control for family background characteristics and schooling. We treat schooling as a choice variable.

Findings: We find that women who were born during the upswing of the demographic cycle would have an incentive to have their first birth earlier and to return to work more quickly (holding schooling constant) than would women who were born during the downswing of the demographic cycle. The findings confirm the predictions of our economic model.

Implications: Our findings indicate that women alter the timing of the first birth and the return to work following that birth in order to mitigate any adverse effects of the demographic cycle on their wage profiles.

#### Introduction

Much of the variation in female life-cycle labor supply across different cohorts of U.S. women born during the twentieth century has been due to changes in the age at which a woman has her first birth and in the length of time spent not working following childbearing. Two contrasting schools have emerged to explain the relationship between the changes in fertility and female labor force participation over time: the "Chicago" school (e.g. Butz and Ward, 1979) focuses primarily on changes in the value of a woman's time (i.e. female wage rates) and the Easterlin school (Easterlin, 1968) focuses on changes in relative income due to the demographic cycle (i.e. the baby boom and baby bust). In this paper we utilize ideas from both schools, and we address empirically the issue of how important the demographic cycle is in explaining the variation in women's ages at first birth and in the duration of time not working following the first birth. The literature suggests that individuals born in different phases of the demographic cycle face different potential wage profiles due to exogenous shifts in the potential supply of labor. Thus the demographic cycle is the direct cause of exogenous wage changes which, in turn, alter the labor force participation and fertility decisions of women.

Most of the empirical work done by other researchers has focused on the consequences of the demographic cycle (and, in particular, the impact of the baby boom) for labor market outcomes--both wages and unemployment. That research has, for the most part, ignored behavioral responses to the constraints imposed by the demographic cycle. We suggest that some individuals may be able to avoid or partially offset any adverse consequences of being born into a large cohort by altering the characteristics with which they enter the labor market or by altering the timing of entry. For example, changes in educational attainment, life-cycle labor force participation, and for women, the timing of marriage and fertility might be optimal responses to the labor market constraints imposed by the demographic cycle.<sup>1</sup>

In this paper we propose a theoretical model in which women alter the timing of their first birth and duration of time not working following that birth in order to mitigate any adverse effects of the demographic cycle on their wage profiles. The model utilizes the idea that the demographic cycle confronts women with different wage profiles depending on when they enter the labor market. The model predicts that (holding schooling constant) women born during the upswing of the demographic cycle have an incentive to begin childbearing earlier and return to work more quickly following child birth than would:women who are born during the downswing of the demographic cycle. We test the predictions of this model and our empirical findings confirm the predictions of the economic model.

We estimate hazard rate models of having a first birth and returning to work subsequent to that birth. We model the timing of these two events as functions of exogenous family background variables, race, predicted education, and measures of the size of the mother's birth cohort. This technique allows us to include observations that are right-censored (i.e. women who have not yet experienced either a first birth or labor market reentry). We use data from three cohorts of the National Longitudinal Surveys of Labor Market Experience (Mature Women, Young Women, and Youth). These data contain information about the age at:first birth and the duration between that birth and labor market reentry for individual women born in various phases of the demographic cycle: 1918-37, 1942-53, and 1957-64. We construct measures of the demographic cycle using information from U.S. Vital Statistics.

2

. ... ×

.

#### Cohort Size and Demographic Behavior

The connection between the demographic cycle and the timing of the first birth and labor market reentry following the first birth can be described very briefly as follows. An increase or decrease in the number of births in a given year will shift (in the same direction) the supply curve of labor 18-20 years later. As long as women with different amounts of labor market experience are not perfect substitutes for one another, this shift will alter the potential wage profile facing a woman in that cohort and will alter the relative attractiveness of home versus market work. The number of potential competitors in surrounding birth cohorts will also affect the benefits of choosing to enter the labor market at an earlier or later time. For example, a woman born during the upswing of the demographic cycle who delays entry into the labor market will compete with the larger cohort that was born a few years later, but earlier entry will mean that she will be in the labor market with the smaller cohort that was born a few years before. The opposite is true for women born during the downswing of a demographic cycle.

There is a consensus in the empirical literature that the present value of life-cycle wages is smaller for workers competing in large cohorts (see Welch, 1979; Freeman, 1979; Berger, 1985; Murphy, Plant, and Welch, 1988; and Falaris and Peters, 1989a).<sup>2,3</sup> Therefore if women do not alter their timing of labor force participation in response to the demographic cycle, women born closer to the peak of the cycle would face worse labor market prospects than women born further from the peak. For example, look at chart 1, which gives the distribution of births over time in the U.S. Women who are born during the earlier part of upswing of the baby boom cycle (e.g., in 1946) would be faced

З

with more favorable labor market prospects than those born during the later part of the upswing of that cycle (e.g., in 1954). Conversely, for women born during the downswing of the demographic cycle, cohorts born earlier (e.g., in 1960). would face worse labor market prospects than cohorts born later (e.g., in 1968).

... 'م<u>ب</u>د

'A woman may be able to choose a more favorable labor market cohort and alter the present value of her lifetime wage stream through two channels: 1) the timing of her first birth and 2) the timing of labor market reentry following the first birth. Thus women born during the upswing of the demographic cycle will want to move away from the peak of the cycle and will have an incentive to try and join an earlier cohort by speeding up the timing of their first birth and the timing of labor market reentry following that birth. Women born during the downswing of the demographic cycle will want to move away from the peak of , the cycle by joining a later cohort and thus slowing down the timing of their first birth and labor market reentry following that birth. 4 If there were no :. costs to changing cohorts then this kind of behavior would lead to perfect arbitrage: women would change cohorts until there was no further return to that activity, and the size of labor market cohorts over time would be equalized. We will assume that there are adjustment costs to changing labor market cohorts which increase with the size of the adjustment, and that there is unobserved heterogeneity in these adjustment costs across different women. The analysis a contact of will thus focus on marginal changes, and these assumptions imply that perfect arbitrage may not occur.

In this section we present a simple partial equilibrium model of these behavioral responses to the demographic cycle. The model abstracts from some of the issues discussed in the more complex birth timing models in the economic literature<sup>5</sup> to focus directly on the possible effects of the demographic

cycle discussed above. First, assume that all women will have one child and that a woman receives utility from lifetime wealth, Z, and from her enjoyment from the child, K. Utility derived from the child is, in turn, a function of the mother's age at childbirth, b, and the length of time the mother spends at home after the child is born, s. Lifetime wealth also depends in a specific way on s and b, and this will be described later. If we assume for simplicity that lifetime utility (U) is separable in Z and K then

(1) U = Z(s,b) + K(s,b).

Assume also that child related utility with respect to the timing of child birth is a function that increases over some range as the age of childbirth increases and then begins to decrease (see figure 2). This assumption can be justified if there are costs to having a child too early. For example, biological and social losses in utility may be higher for teenage mothers than for women who give birth in their 20's. Eventually, however, costs of child bearing (and the probability of giving birth to a child with serious birth defects) may begin to rise as a woman approaches the limits of her "biological clock." Child related utility is also assumed to rise at a decreasing rate with the length of time spent at home after childbirth (see figure 1). This assumption relates to the idea that mothers receive some benefit from spending time at home with the child and watching the child grow. Mother's time is also an important input into the production of child quality, especially when the child is very young.

Choices about s and b also enter indirectly into the utility function through their effect on wages and lifetime wealth. In this model a woman can receive two types of wages: unskilled and career wages. Unskilled wages  $(\tilde{w}(t))$ are solely a function of the labor market conditions in the current

period, t. Because unskilled workers with different levels of experience are perfect substitutes for one another, wages depend on the total supply of unskilled workers in the population and are independent of the size of the unskilled worker's cohort. Wages in "career" jobs are modeled as a function of <u>t</u>. years of experience of the worker, E, and the labor market cohort to which an individual belongs, C:

· . .

(2) w = w(E,C) where  $\partial w/\partial E > 0$ 

Note that C represents the date of the cohort along a time line rather than the size of that cohort. For individuals born during the upswing of the demographic cycle, a small increase in C implies joining a cohort closer to the peak of the cycle with lower wage prospects, i.e.,  $\partial w/\partial c < 0$ . For individuals born during the downswing of the demographic cycle, a small increase in C implies joining a cohort further away from the peak of the cycle with more favorable wage prospects, i.e.,  $\partial w/\partial c > 0$ .

To illustrate how individuals may be able to choose their labor market cohort we first characterize three distinct types of workers: 1) continuous workers; 2) traditional mothers; and 3) career interrupters. Continuous workers enter the labor market at age m (which is assumed to be exogenous and invariant across individuals in different birth cohorts)<sup>6</sup> and work continuously until retirement at age R. The life cycle labor force patterns of most men and of permanently childless women are examples of this type of worker. The labor market cohort for these workers is defined as i+m, the date at which a continuous worker who is born in year i enters the labor force. By assumption continuous workers do not alter their life cycle labor supply in response to the demographic cycle.

The life cycle labor supply of traditional mothers is divided into three segments: 1) she works full time prior to the birth of the child (age m to age b); 2) she works zero hours for some period of s years following that birth; and 3) after she returns to the labor force (at age b+s) she works full time until retirement. It is often argued that prior to childbearing women have a disincentive to invest in on-the-job training, because specific human capital depreciates during the period of time spent out of the labor force after the birth of a child. In the extreme, this picture of the "traditional" mother implies that prior to childbearing she would receive an unskilled or spot market wage, w(t) and would wait until after the childbearing period to begin a career. Her labor market cohort is defined as the date at which she begins a career, i+b+s, her date of birth plus the age at which she returns to work after having a child. Compared to a continuous worker she delays her relevant labor market cohort by b+s-m years. Thus at any date,  $t \ge i+b+s$  she is assumed to compete in the same labor market cohort (i.e. have the same level of experience) as a continuous worker born in cohort i+b+s-m.

Career interrupters are defined as delayed childbearers who first begin a labor market career at age m prior to having a child, then drop out of the labor market for a period of time to have the child, and finally resume their careers at age b+s. This type of labor force pattern has become more common in recent years. Note that at the limit career interrupters become continuous workers when s approaches zero. The wage profile for these women is broken into two parts--pre and post childbearing-- and each part is determined by a different labor market cohort. If we make the extreme assumption that there is no depreciation of human capital during the period of time spent out of the labor

force, then career interrupters will have the same incentive to invest in onthe-job training, the same rate of return to experience, and the same early wage profiles as continuous workers who are born in their cohont. When the career interrupter born in cohort i reenters the labor force at date i+b+s with b-m years of experience, she has the same level of experience as a continuous worker who was born in cohort i+s, and she is a member of labor market cohort i+s+m. Thus all individuals who at any date t have the equal amounts of experience in a career job are defined to be members of the same labor market cohort.

Lifetime wealth for the "traditional" life-cycle labor supply pattern where the true career begins after childbirth can be written as follows:

$$i+b - \dots i+b+s = i+R$$
(3) 
$$Z = \int [v(t) + w(t)]dt + \int [v(t)dt + \int [v(t) + w(i+b+s,t-i-b-s)]dt = 0$$

$$i+m = i+b = i+b+s$$

where V(t) represents non-wage income, i+b is the date of childbirth, i+b+s:is the date at which the woman returns to work following childbirth, i+R is the date of retirement, and m is the age the woman begins market work (note that m must be less than or equal to b, the age of childbirth). Labor supply is equal to 1 during period of work and 0 otherwise. For simplicity, the interest rate is assumed to be zero. In the first term in equation (3) the income a woman receives prior to childbearing is equal to non-wage income plus earnings from an unskilled job. In the second term her income is just equal to non-wage income, because she is not working during that period. During the third:segment of ther life-cycle a woman begins a career in which her wage depends on experience and her labor market cohort. Because her prior labor market experience was in an unskilled job, we assume that the relevant career experience (the second argument in the career wage function) is zero when she begins a career at

Ł 7.

date i+b+s. Similarly, the relevant cohort (the first argument in the career wage function) is the date at which she begins her career.

Substituting (3) into the utility function specified in (1) we maximize utility with respect the two choice variables s and b and obtain the following first order conditions:

(4)  $w(i+b+s,0) + \int (\partial w/\partial E - \partial w/\partial c)dt = \partial k/\partial s$  and i+b+s (a) (c) (d)

 $\begin{array}{rcl} & & & i+R \\ (5) & w(i+b+s,0) & - & w(i+b) + \int (\partial w/\partial E & - & \partial w/\partial c) dt = & \partial k/\partial b. \\ & & & i+b+s \\ (a) & (b) & (c) & (d) \end{array}$ 

Equation (4) gives the conditions for the optimal choice of s. Term (a) is the opportunity cost of lost career wages from increasing s by one unit. Term (c) is the cost due to lost experience from increasing s by one unit. The experience cost is summed over the entire remaining working lifetime of the woman. Term (d) is the cohort slippage effect of increasing s by one unit. This term is also summed over the entire remaining lifetime of the woman. As described above, this term will be negative or positive depending on whether the woman is born on the upswing or the downswing of the demographic cycle. At the optimum the net marginal cost in terms of lost lifetime wealth (the left hand side of equation 4) is equal to the marginal child related benefits from an increase in s.

Figure 1 shows the tangency condition implied by equation (4) and can be used to illustrate the effect of the demographic cycle on the optimal choice of s. For individuals born on the upswing of the demographic cycle the cohort slippage effect is negative  $(\partial w/\partial c < 0)$  which leads to an increase in the wealth

related marginal cost of more s. For these individuals the tangency will occur at a steeper part of the marginal benefit curve and produce an optimal s at a point like  $s_u$ . For individuals born on the downswing of the demographic; cycle the cohort slippage effect is positive, the marginal wealth cost is lower, and  $s_d$  is greater than  $s_u$ .

The choice of the timing of child birth can be analyzed in a similar way. In equation (5) the marginal effect of b on wealth contains terms which capture the experience cost (c) and cohort slippage effect (d) discussed above. The remaining terms represent the difference between the unskilled wage a woman would receive just prior to childbirth and the beginning career wage she would receive after reentering the labor market. This net marginal cost (benefit) in terms of wealth is set equal to the marginal child related benefit (cost) from increasing b. As before the cohort slippage effect for women born during the upswing of the demographic cycle is negative, increasing marginal wealth costs (or reducing marginal benefits). The tangency condition would lead to a choice of b such as  $b_u$  in figure 2. A positive cohort slippage effect for women born during the downswing of the demographic cycle would reduce marginal wealth costs and lead to a choice of birth timing such as  $b_d$  where  $b_d > b_u$ .

Lifetime wealth for a career interrupter can be written as follows:

 $i+b i+b+s i+R (6) Z = \int [v(t) + w(i+m,t-i-m)]dt + \int [v(t)dt + \int [v(t) + w(i+m+s,t-i-s-m)]dt + m i+b i+b+s i+b+s$ 

As described above, the career wage path for these women is broken intortwo, parts and each part is governed by a different labor market cohort. Substituting (6) into the utility function specified in (1) and maximizing utility with respect to s, we find that the first order condition for the

optimal choice of s is identical to equation (4). Career interrupters born on the upswing of the demographic cycle have an incentive to speed up the timing of their labor market reentry following childbirth and women born during the downswing of the cycle have the opposite incentives regarding s. Interestingly, we observe that the birth timing decision, b, does not enter as a determinant of the cohort argument in the wage function. Therefore the demographic cycle will have no effect on the timing of childbirth for women who can be characterized as career interrupters.

The analysis presented above implies that choices about the timing of reentry to the labor market can be used by all types of women to alter their labor market cohort, but that the effect of the timing of childbearing on labor market cohort depends, in part, on how we treat pre-childbearing labor market experience. We have described two extreme cases. For the traditional mother none of the pre-childbearing market experience counts, and upon reentry she is considered to be the same as a brand new entrant. The longer she delays childbearing and the beginning of her career, the greater is the cohort slippage effect. For the career interrupter all the pre-childbearing experience counts, and when she reenters the market she competes with a group of individuals who have the same labor market experience that she had when she first left the market. Thus the delay in her career and the cohort slippage effect is solely a function of the length of time she spends out of the labor force after childbearing. In general many women are likely to be some combination of our two extreme cases. Some years of effective experience may be lost due to depreciation of specific human capital while out of the labor force. Upon reentry this woman will be competing with a group of individuals who have slightly less experience than she had reached just before dropping out of the labor force. If the extent of this depreciation is a positive function of the

amount of her pre-childbearing experience, then birth timing decisions may to some extent be able to affect the choice of labor market cohort for career interrupters.

To summarize the empirical implications of the model, we predict that women: born during the upswing of the demographic cycle will have their births earlier and will return to work more quickly. Women born during the downswing of the demographic cycle will delay their first birth and their labor market reentry. We also expect the response of the timing of labor market reentry to the demographic cycle to be larger than the response of birth timing.<sup>7</sup>

The delayed childbearing of the baby boom generation might, on the surface, seem to contradict the hypotheses proposed above. Baby boom women, however, are also getting more schooling (Falaris and Peters, 1989a, b) which tends to be associated with later childbearing. This educational effect could partially or totally offset any tendency towards earlier childbearing associated with the woman's position in the demographic cycle. Our theoretical model takes schooling decisions and the age of labor market entry as exogenous. In cur empirical work we utilize results from our previous paper to account for the endogeneity of schooling choices, and we disentangle the <u>marginal</u> effect of cohort size on age at first birth (i.e. conditional on predicted education) from the <u>total</u> effect which includes the offsetting schooling and cohort wage : effects.

In the econometric specification of age at first birth and timing of labor, market reentry we control for the effect of exogenous family background characteristics, education, and relative cohort size. In other literature several kinds of measures have been used to capture the effects of the demographic cycle: 1) number of individuals born in a given year (own birth

cohort): 2) an indicator of the part of the demographic cycle during which an individual is born, e.g., the beginning, peak, or end of the cycle (relative cohort size); 3) number of labor force participants in a given year (labor market cohort). In the empirical work we use the second measure for two reasons. First, this measure can be regarded as exogenous from the point of view of the individual. In contrast, measures of labor market cohort used by Welch (1979), Berger (1985), and Freeman (1979) are, in our specification, choice variables. Relative cohort size is also more appropriate than absolute cohort size in a model that focuses on the timing of fertility and labor market reentry. It is the number of individuals born just prior and after one's own cohort that determines how easily a woman can alter the labor market opportunities she faces by changing the timing of demographic behavior such as first birth. We represent relative cohort size by two variables, past and future cohort size. These are defined as the ratios of own cohort size to preceding (past) and subsequent (future) cohorts, each averaged over five years:

For individuals born during the upswing of the demographic cycle, Past is greater than one and Future is less than one. The opposite is true for individuals who are born during the downswing of the demographic cycle.

Household production theory predicts that non-wage income (e.g. husband's income or other family income) should affect the value of home time, and, as a consequence, age at first birth and the timing of labor market reentry. We do not control for income for the following reasons. First, income varies over time, and Heckman and Singer (1984a) state that hazard rate estimates are

sensitive to the specification of the discretization of time-varying covariates. Secondly, whether or not to marry and who to marry are choice variables, and these choices may also be influenced by the constraints imposed by the demographic cycle. Inclusion of these endogenous variables will produce inconsistent estimates of the age at first birth and timing of labor market reentry. Modeling these marriage choices explicitly is beyond the scope of this paper. In our specification, the effect of these marital choices will thus be captured indirectly through family background variables and cohort size which, in part, determine marital choices.

#### Data and Empirical Estimation

We estimate the model for the timing of the first birth using observations on 10,386 U.S. women born from 1918-1964. The observations are drawn from three cohorts of the National Longitudinal Surveys of Labor Market Experience. (Mature Women, Young Women, and Youth). These cohorts are nationally representative samples of women born during the downswing of the demographic cycle of the 1930's, the upswing of the demographic cycle of the mid 1940's-1957 (the baby boom), and the downswing of the demographic cycle following its peak in 1957 (see Chart 1). 70 percent of the women in the sample have had a first birth before the end of the observation period (although only 55: percent of the women in the youth cohort had a first birth, so for that sample the right censoring is more severe). We estimate a hazard model to study the effect of the demographic cycle on the interval from age 12 to a woman's age at her first birth (the first birth interval). If we assume that the first birth interval, T, has the extended generalized gamma distribution, then the log of the first birth interval can be written as  $Y = log(T) = \delta X + \sigma W$ , where X is a matrix of

1 2- -5

÷ ].

regressors, A is a vector of parameters (including a constant),  $\sigma$  is a scale parameter, and W is a random variable which has the extended generalized gamma distribution (Lawless, 1982, p. 240). The density function of W (note that W = (Y-  $\beta X/\sigma$ ) is

(8) 
$$f(w, \alpha) = \frac{|\alpha|}{\Gamma(1/\alpha^2)} (\alpha^{-2}) \exp(\alpha^{-2}(\alpha w - \exp(\alpha w))) - \omega < w < \infty$$

 $\Gamma$  is the complete gamma function and  $\alpha$  the gamma shape parameter. This distribution nests the gamma, lognormal, Weibull, and exponential distributions as special cases. We can test this more general distribution against the special cases by imposing restrictions on the parameters  $\alpha$  and  $\sigma$  testing them statistically. To use both censored and uncensored observations (i.e. women who have not had a first birth by the most recent observation period, but who are likely to have a birth sometime in the future) we specify the following loglikelihood function:

(9) 
$$\log L(\beta, \sigma, \alpha) = \Sigma (\log f(w, \alpha) - \log \sigma) + \Sigma (\log(1 - F(w, \alpha)))$$
  
ieB ieC

where f(.) is the density function, 1-F(.) is the survivor function (the complement of the CDF of W), B denotes completed or uncensored first birth intervals, and C denotes censored first birth intervals.

Using maximum likelihood methods we estimate the parameters  $\alpha$ ,  $\beta$ , and  $\sigma$ , and we test the restrictions on  $\alpha$  and  $\sigma$ . Likelihood ratio tests indicate that the more general extended generalized gamma model is the correct model. Tables 1 and 2 report summary statistics, definitions of the variables and years of last observation for each data set. Estimates of the model for the first birth interval, conditional on schooling, are reported in Table 3.

The regressors include exogenous individual family background characteristics, two relative cohort size variables and predicted education. In this model education is an endogenous variable which is affected by relative cohort size (see Falaris and Peters, 1989a, b, for a justification of this treatment), so we replace that variable by its predicted value to obtain .... consistent parameter estimates. Predicted education is obtained by using the coefficient estimates of the education equation for women which is reported in Appendix Table 1 (this is similar to the education equation reported in Falaris and Peters, 1989a, except that here we include Mature Women's data as well as data for younger women). The identifying restriction is that her parents' educational attainments are assumed to affect a woman's educational attainment but not her first birth interval (except indirectly through education). In Appendix Table 2 we report estimates of a model for the first birth interval. which contains only exogenous regressors and thus requires no exclusionary identifying restrictions.

In our previous paper we found that a woman would increase her educational attainment in response to a baby boom. Our results indicated that cohort size affects educational choices by altering the relative rate of return to education for individuals born during different phases of the demographic cycle. In contrast, in the theoretical model presented above, cohort size operates on fertility primarily through its effect on the timing of fertility. We hypothesize in the present study that, conditional on education, a woman born during the upswing of the demographic cycle would shorten the first birth interval. It is unclear what sign the relative cohort size coefficients should have in the reduced form, since they capture two opposing influences. The first birth model which is conditional on schooling allows us to test the existence of a pure demographic cycle effect on the timing of the first birth.

The main results in Table 3 are that an increase in a woman's education increases the first birth interval (see Bloom, 1982, for similar results), and that both future and past relative cohort size significantly affect the first birth interval. In particular, being born during the upswing of the demographic cycle (Past > 1 and Future < 1) has the marginal effect of shortening the first birth interval. Conversely, for individuals born during the downswing of the demographic cycle (Past < 1 and Future > 1) the first birth interval is longer. These results are consistent with the hypothesis that one of the ways in which women attempt to mitigate the adverse effects of a baby boom on their wages is through the timing of fertility. In Appendix Table 2, the relative cohort size coefficients have the same signs as the structural ones but are smaller in absolute value and only one is significant. This result is not surprising since the relative cohort variables capture two opposing influences.

According to the estimates in Table 3, a white woman is predicted to have a longer first birth interval than a nonwhite woman. This result is consistent with other evidence on the relationship between race and age of childbearing (see, e.g., Bloom, 1982). The results also indicate a negative relationship between the number of siblings a woman has and the length of her first birth interval. This result could be due to a correlation in family size across generations. If women with a large number of siblings also have tastes for a larger family, they will begin their childbearing at an earlier age. We also estimated a similar model which included a trend variable. Its coefficient was not significant at the ten percent level, so the trend was omitted.

Table 4 reports estimates of the return to work model. The time interval is measured in months from the first birth until the return to work. We do not distinguish between being out of the labor force and being unemployed but treat them as a common state (not working). We use data on the 6,321 women who have

had a first birth and for whom it is possible to calculate the return to work interval. The proportions of women who have returned to work by the end of the observation period are 67%, 78%, and 80% for the mature women, young women and youth, respectively. The mature women were asked a retrospective question on the timing of their return to work following their first birth at the beginning of the survey.<sup>8</sup> For the young women and youth subsamples we use employment history information to calculate the return to work intervals. 9 In all three surveys some women report that they never stopped working after their first birth (most of these women probably were on a brief maternity leave and returned to work for the same employer). We assign a value of one month to these intervals so we can calculate their natural logarithm. We estimate positive and negative coefficients for Future and Past relative cohort size variables, respectively. This indicates that women born on the upswing of the demographic cycle tend to shorten their return to work intervals while women born during the downswing of the demographic cycle do the opposite. Our estimates confirm the predictions of the model in the previous section. White women and women who grew up in urban areas tend to return to work later than other women (these may reflect income effects), and there is a strong negative trend (implying shorter return to work intervals). We find no significant effect of predicted . education.

In Appendix Table 3 we report estimates of a return to work model which contains only exogenous regressors and thus needs no exclusionary identifying restrictions of the sort required for the model which is conditional on schooling. The estimates are generally highly similar to those in Table 4. The coefficient estimates for Future and Past Relative Cohort Size are within one a standard error of the corresponding estimates in the two tables.

<u>Heterogeneity</u>

Two observationally identical women may have different first birth (return to work) intervals because they differ in ways which are not observed by the investigator (unobserved heterogeneity). Neglecting such unobserved heterogeneity may result in biased coefficient estimates of the statistical models such as ours even if the heterogeneity is uncorrelated with the included regressors of the models (Heckman and Singer, 1984a). Some previous studies (e.g. Lancaster, 1979; Even, 1987) have modeled heterogeneity as following some parametric distribution such as gamma or beta logistic whose parameters can be estimated from the data. Heckman and Singer (1984a, 1984b) have argued that the results in these studies are highly sensitive to the distributional assumptions about heterogeneity and have proposed a method of controlling for heterogeneity which imposes very weak distributional assumptions. Their method, minimizes the impact of distributional assumptions on the estimates of the model.

We implement the method of Heckman and Singer as follows. We assume that the first birth interval (return to work interval) is  $Y = log(T) = \theta_i + \beta X + \sigma W$ , (B does not include a constant term) where  $\theta_i$  is a parameter (constant term) drawn from a discrete distribution with points of support  $\theta_1, \theta_2, \ldots, \theta_K$  and associated probabilities  $P_1, P_2, \ldots, P_K$  (the  $P_i$  sum to one). In other words the probability is  $P_i$  that an individual drawn from the population at random will have a constant term  $\theta_i$ .

Controlling for heterogeneity, the likelihood function becomes

(10)  $\log L(.) = \sum (\log(\sum P_j f_{ij}(.)) - \log \sigma) + \sum (\log(\sum P_j (1-F_{ij}(.))))$  $i \in B$   $i \in C$  j j j  $i \in C$ 

where j indexes the points of support of  $\theta$ . We treat as an empirical matter how many points of support  $\theta$  will be specified as having by estimating models in which we increase the number of points of support until there is no significant increase in the value of the log-likelihood. Thus we specify a model for the first birth interval with three points of support for  $\theta$  and a model for the return to work with four points of support. The estimates of these models are reported in Tables 5 and  $\theta^{10}$ . For both models the value of the log-likelihood is much higher than in the corresponding models without heterogeneity in Tables 3 and 4.<sup>11</sup> This indicates the presence of significant unobserved heterogeneity. The estimates of the slope coefficients, however, do not differ very much in the specification with and without heterogeneity. The estimates of the coefficients of future and past relative cohort size are within one standard error of each other in the models which allow for heterogeneity and those that do not for both the first birth and return to work models.

It is instructive to look at some predictions obtained using the parameters of this model which allows for heterogeneity. The weighted survivor function,  $\sum_{j=1}^{r} P_{j}(1-F(t))$ , gives the predicted proportion of women who have not had a first birth by age t. This statistic is the simplest way to illustrate the impact of cohort size on fertility decisions. We can compare the weighted survivor function calculated using our estimated coefficients for observationally identical women born during different phases of the demographic cycle. For a woman with sample mean characteristics who was born in 1951 (during the upswing of the demographic cycle) the value of the survivor function at age 24.3 is 0.499. This means that we predict that 49.9 percent of these women have not had a first birth by the age of 24.3 (this age is chosen because it is the mean age at first birth in the sample). For a woman with mean characteristics born in

: .= . .

1964 (during the downswing of the demographic cycle) the predicted value of the survivor function of 0.535. Fewer women born during the upswing of the demographic cycle have not had a birth by the age of 24.3 (i.e. the first birth interval is shorter) relative to women born during the downswing of the demographic cycle. These survivor functions are depicted in Chart 2. Chart 3 presents survivor functions for the return to work following the first birth for women with sample mean characteristics born in 1951 and in 1964, respectively. In evaluating these survivor functions we abstract from trend effects by setting the trend equal to its sample mean. The results are similar to those obtained for the first birth interval. At 3.6 years since first birth the value of the survivor function is 0.510 for women born in 1951. For women born in 1964 the predicted value of the survivor function is 0.556. Thus we predict a shorter return to work interval for women born during the upswing of the demographic cycle than for women born during the downswing of the demographic cycle.

#### Conclusion

In this paper we propose a model according to which women alter the timing of the first birth and the return to work following that birth in order to mitigate any adverse effects of the demographic cycle on their wage profiles. We predict that women who were born during the upswing of the demographic cycle would have an incentive to have their first birth earlier and to return to work more quickly (holding schooling constant) than would women who were born during the downswing of the demographic cycle. Our empirical evidence confirms these predictions.

The behavioral responses to the demographic cycle described in this paper have implications for the dramatic changes that have occurred over the past few decades in the labor force participation rates of mothers with young children. Some of the increase in these rates during the later 1960s and 1970s can be explained by the incentives to return to work more quickly for women who were born during the upswing of the demographic cycle. Our results indicate, however, that the increase in participation rates during the 1980s might well have been even larger if women born during the downswing of the demographic cycle did not have incentives to delay their return to work following childbearing.

#### Endnotes

In previous research (Falaris and Peters, 1989a,b) we focus on 1. educational choices -- both the timing and level of educational attainment. In that research we find that both men and women alter their schooling in response to the demographic cycle. In addition, we find that the increase in schooling in response to the baby boom mitigates the adverse direct effect of cohort size on wages. The magnitude of the educational response and the extent of mitigation due to this response, however, is much larger for men than for women. The puzzle posed by this last result of our previous research is the starting point for this paper. Why is the effect smaller for women than for men? We suggest that women have additional behavioral responses to the demographic cycle that are less available for men. In particular, patterns of labor force participation are more variable for women than for men; women can alter their life-cycle labor supply through changing their number of children, the timing of childbearing, and the timing of reentry to the labor market following the birth of a child.

2. There is still, however, some debate over the size of the cohort penalty over the life cycle. Berger (1984, 1985) argues that wage profiles are also flatter for workers in large cohorts. Thus the cohort penalty increases over the life cycle. Murphy, Plant, and Welch (1988) make the opposite argument.

3. Because most of the evidence on cohort size and wages is for men, there is as yet no clear consensus about the effect of the demographic cycle on female wages. Freeman (1979) finds no effect of cohort size for women. Using more recent data, however, Falaris and Peters (1989a) do find a significant effect of cohort size on women's wages.

4. This basic timing argument was first proposed by Wachter and Wascher (1984). They apply the argument to decisions about schooling. In our previous work (Falaris and Peters, 1989a, b) we find evidence that individuals do alter schooling choices in response to the demographic sycle, but that the timing of schooling is not the primary response.

5. See, for example, Razin (1980) and Newman and McCulloch (1984). We ignore issues of consumption smoothing, spacing of births, and the interaction of timing with the demand for numbers of children.

5. In our empirical work we relax this assumption by treating schooling as endogenous.

7. Some women will have more than one birth. The general implications of our economic model may hold in these cases also. Data on spacing of subsequent births and female life cycle labor supply, however, are not available over a long period of time. Therefore, we do not deal with these issues.

8. However, 99% of all first births to these women who are in our fertility sample had taken place by the beginning of the survey so the amount of information lost by ignoring return to work intervals for births occurring after 1967 is quite small.

9. For the young women we can do this only for the period 1968-1983.

10. We do not report standard errors for the model in Table 5 because of numerical difficulties in their estimation. The standard errors in Tables 5 and 6 are evaluated numerically because of the great complexity of the analytical derivatives. In these cases it is possible that the numerically evaluated hessian may be singular at the function optimum making it impossible to obtain estimates of the standard errors of the parameters. This occurs for the model in Table 5 but not for the model in Table 6. We attempted to estimate the model in Table 5 using a variety of alternative optimization computer programs: the function minimization routines of LIMDEP; a variety of algorithms of GQOPT; the hessian approximation subroutines in both the IMSL and NAG libraries. In all cases the estimated hessian was singular. In any case, the (point) estimates of the slope coefficients in Table 5 do not differ very much from those in Table 3.

11. A likelihood ratio test is not applicable in this case because it would involve testing a restriction on the boundary of the parameter space.

Table 1. Means and Standard Deviations of the Variables<sup>a</sup>

| Variable                            | Mean Standard Deviation |         |  |
|-------------------------------------|-------------------------|---------|--|
| Time to First Birth <sup>b</sup>    | 147.342                 | 77.341  |  |
| White                               | 0.763                   | 0.425   |  |
| Father's Education                  | 10.044                  | 4.053   |  |
| Mother's Education                  | 10.360                  | 3.308   |  |
| Predicted Education                 | 12.494                  | 1.360   |  |
| Urban                               | 0.743                   | 0.437   |  |
| Siblings                            | 3.689                   | 2.682   |  |
| Future Relative Cohort Size         | 1.019                   | 0.072   |  |
| Past Relative Cohort Size           | 1.021                   | 0.075   |  |
| Time to Return to Work <sup>C</sup> | 43.063                  | 55. 408 |  |

<sup>a</sup>The summary statistics of all the variables other than Time to Return to Work are based on the sample used for the estimation of the model for the first birth interval.

<sup>b</sup>Time in months from age 12 to the time of the first birth. For women who have not had a first birth by the end of the observation period the time of the last observation is included in the calculation of these summary statistics.

<sup>C</sup>Time in months from the first birth to the return to work. For women who have not returned to work by the end of the observation period the time of the last observation is included in the calculation of these summary statistics.

| Data Set.                                 | •  |  |  |
|---|--|--|--|
| A. Variable Definitions                   |  |  |  |
| White                                     | 1 if white and 0 otherwise   |  |  |
| Urban                                     | l if a woman lived in an<br>urban area at age 14 (Young<br>Women, Youth) or age 15<br>(Mature Women) and O otherwise   |  |  |
| Father's Education,<br>Mother's Education | in single years  |  |  |
| Predicted Education                       | prediction obtained using<br>each individual's<br>characteristics and the<br>parameters of the education<br>equation for women reported<br>in Appendix Table 1 |  |  |
| Future Relative Cohort Size               | defined in the text  |  |  |
| Past Relative Cohort Size                 | defined in the text  |  |  |
| Prewar                                    | 1 if born before 1945, 0 otherwise   |  |  |
| Postvar                                   | 1 if born in or after 1945, O otherwise P  |  |  |
| Trend                                     | time elapsed between 1900 and a woman's<br>year of birth   |  |  |

Table 2. Variable Definitions and Years of Last Observation for Each

#### B. Years of Last Observation

|              | First Birth | Return to Work |
|--------------|-------------|----------------|
| Mature Women | 1982        | 1967           |
| Young Women  | 1985        | 1983           |
| Youth        | 1987        | 1987           |

Note: these dates are upper bounds for the data sets. Some individual women dropped out of the survey at earlier dates which are known.

| Constant                  | 3.260**   | · · · · · · · · · · · · · · · · · · · |
|---------------------------|-----------|---------------------------------------|
| (t-statistic)             | (20.061)  |                                       |
| White                     | 0.215**   |                                       |
|                           | (14.835)  | · ·                                   |
| Predicted Education       | 0.105**   |                                       |
|                           | (19.552)  |                                       |
| Urban                     | 0.002     | · · · · · · · · · · · · · · · · · · · |
|                           | (0.126)   |                                       |
| Siblings                  | -0.004+   | ·.                                    |
| -                         | (-1.690)  |                                       |
| Future Relative           | 0.308++   |                                       |
| Cohort Size               | (3.353)   |                                       |
| Past Relative             | -0.158*   |                                       |
| Cohort Size               | (-1.803)  |                                       |
| Scale Parameter (σ)       | 0.585**   | •                                     |
|                           | (115.981) |                                       |
| Gamma Shape Parameter (a) | -0.513++  |                                       |
|                           | (-23.006) |                                       |
| Log-Likelihood            | -8688.232 |                                       |
| Sample Size               | 10, 386   |                                       |
|                           |           |                                       |

Table 3. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the First Birth Interval, Conditional on Schooling.

Significantly different from zero at the 5 percent level Significantly different from zero at the 10 percent level

| (t-statistic)       (7.906)         White       0.338**         (6.310)       Predicted Education         Predicted Education       -0.002         (-0.101)       (-0.101)         Urban       0.151**         (2.911)       Siblings         Siblings       0.014         (1.509)       Future Relative         Cohort Size       (2.095)         Past Relative       -0.888**         Cohort Size       (-2.399)         Trend       -0.048**         (-20.745)       Scale Parameter (α)         Scale Parameter (α)       0.223** | Constant                                   | 5.303**             | *************************************** |
|---|--|---------------------|---|
| White       0.338**         (6.310)         Predicted Education       -0.002         (-0.101)         Urban       0.151**         (2.911)         Siblings       0.014         (1.509)         Future Relative       0.825**         Cohort Size       (2.095)         Past Relative       -0.888**         Cohort Size       (-2.399)         Trend       -0.048**         (-20.745)       Scale Parameter (α)         Scale Parameter (α)       0.223**   | (t-statistic)                              | (7.906)             |   |
| Infect       (6.310)         Predicted Education       -0.002         (-0.101)       (-0.101)         Urban       0.151**         (2.911)       (2.911)         Siblings       0.014         (1.509)       (1.509)         Future Relative       0.825**         Cohort Size       (2.095)         Past Relative       -0.888**         Cohort Size       (-2.399)         Trend       -0.048**         (-20.745)       Scale Parameter (σ)         Scale Parameter (σ)       1.670**         Gamma Shape Parameter (α)       0.223** | White                                      | 0.338 <del>**</del> |   |
| Predicted Education       -0.002<br>(-0.101)         Urban       0.151**<br>(2.911)         Siblings       0.014<br>(1.509)         Future Relative<br>Cohort Size       -0.825**<br>(2.095)         Past Relative<br>Cohort Size       -0.888**<br>(-2.399)         Trend       -0.048**<br>(-20.745)         Scale Parameter (σ)       1.670**<br>(65.038)         Gamma Shape Parameter (α)       0.223**  | 17 A 4 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 | (6.310)             |   |
| (-0.101)         Urban       0.151**         (2.911)         Siblings       0.014         (1.509)         Future Relative       0.825**         Cohort Size       (2.095)         Past Relative       -0.888**         Cohort Size       (-2.399)         Trend       -0.048**         (-20.745)       Scale Parameter (σ)         Scale Parameter (σ)       1.670**         Gamma Shape Parameter (α)       0.223**  | Predicted Education                        | -0.002              |   |
| Urban       0.151**         Siblings       0.014         Siblings       0.825**         Cohort Size       (2.095)         Past Relative       -0.888**         Cohort Size       (-2.399)         Trend       -0.048**         (-20.745)       Scale Parameter (α)         Scale Parameter (α)       0.223**         Gamma Shape Parameter (α)       0.223**  |  | (-0.101)            |   |
| (2.911)         Siblings       0.014<br>(1.509)         Future Relative<br>Cohort Size       • 0.825**<br>(2.095)         Past Relative<br>Cohort Size       • 0.888**<br>(-2.399)         Trend       • 0.048**<br>(-20.745)         Scale Parameter (α)       1.670**<br>(65.038)         Gamma Shape Parameter (α)       0.223**   | Urban                                      | 0.151**             |   |
| Siblings       0.014<br>(1.509)         Future Relative<br>Cohort Size       0.825**<br>(2.095)         Past Relative<br>Cohort Size       -0.888**<br>(-2.399)         Trend       -0.048**<br>(-20.745)         Scale Parameter (σ)       1.670**<br>(65.038)         Gamma Shape Parameter (α)       0.223**   |  | (2.911)             |   |
| (1.509)         Future Relative         Cohort Size         Past Relative         Cohort Size         Cohort Size         Trend         -0.048**         (-20.745)         Scale Parameter (σ)         I.670**         (65.038)         Gamma Shape Parameter (α)         0.223**   | Siblings                                   | 0.014               | •                                       |
| Future Relative<br>Cohort Size• 0.825**<br>(2.095)Past Relative<br>Cohort Size-0.888**<br>(-2.399)Trend-0.048**<br>(-20.745)Scale Parameter (σ)1.670**<br>(65.038)Samma Shape Parameter (α)0.223**<br>(0.223**  |  | (1.509)             |   |
| Cohort Size     (2.095)       Past Relative     -0.888**       Cohort Size     (-2.399)       Trend     -0.048**       (-20.745)       Scale Parameter (σ)     1.670**       Gamma Shape Parameter (α)     0.223**  | Future Relative                            | • 0.825++           |   |
| Past Relative<br>Cohort Size       -0.888**<br>(-2.399)         Trend       -0.048**<br>(-20.745)         Scale Parameter (σ)       1.670**<br>(65.038)         Samma Shape Parameter (α)       0.223**   | Cohort Size                                | (2.095)             |   |
| Cohort Size     (-2.399)       Trend     -0.048**       (-20.745)       Scale Parameter (σ)     1.670**       (65.038)       Samma Shape Parameter (α)     0.223**  | Past Relative                              | -0.888**            |   |
| Trend       -0.048**         (-20.745)         Scale Parameter (σ)       1.670**         (65.038)         Samma Shape Parameter (α)       0.223**   | Cohort Size                                | (-2.399)            | ,                                       |
| (-20.745)<br>Scale Parameter (σ) 1.670**<br>(65.038)<br>Gamma Shape Parameter (α) 0.223**   | Trend                                      | -0.048++            |   |
| Scale Parameter (σ)       1.670**         (65.038)       (65.038)         Gamma Shape Parameter (α)       0.223**         (α)       0.223**   | •  | (-20.745)           |   |
| (65.038)<br>Gamma Shape Parameter (α) 0.223**   | Scale Parameter (ơ)                        | 1.670**             |   |
| Gamma Shape Parameter (a) 0.223**   |  | (65.038)            |   |
|   | Gamma Shape Parameter (a)                  | 0.223**             | е '<br>ж. т.                            |
| (3.794) ~   |  | (3.794) -           | <u>۲</u> .                              |
| Log-Likelihood -10735.147   | Log-Likelihood                             | -10735.147          |   |
| Sample Size 6,321   | Sample Size 🛶 👘                            | 6, 321              |   |

Table 4. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the Return to Work Interval Following the First Birth, Conditional on Schooling.

\*\* Significantly different from zero at the 5 percent level

Significantly different from zero at the 10 percent level.

| White                          | 0.229               |         |
|--------------------------------|---------------------|---------|
| Predicted Education            | 0.105               | •       |
| Urban                          | 0.009               | · · · · |
| Siblings                       | -0.004              | ,       |
| Future Relative<br>Cohort Size | 0.337               |         |
| Past Relative<br>Cohort Size   | -0. 188             |         |
| θl                             | 3. 098              |         |
| θ2                             | 2.577               | ·       |
| θ <sub>3</sub>                 | 3. 295              |         |
| P <sub>1</sub>                 | 0.245               |         |
| P <sub>2</sub>                 | 0.013               |         |
| Scale Parameter (g)            | 0.578               |         |
| Gamma Shape Parameter (a)      | -0.711              |         |
| Log-Likelihood<br>Sample Size  | -8632.567<br>10,386 |         |
|                                |                     |         |

Table 5. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the First Birth Interval, Conditional on Schooling, with Heterogeneity.

Table 6. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the Return to Work Interval Following the First Birth, Conditional on Schooling, with Heterogeneity.

| White `             | 0.220**             | Ρ.                  | 0.106++  |         |
|---------------------|---------------------|---------------------|----------|---------|
| (t-statistic)       | (5,297)             | 1                   | (3.113)  |         |
|                     |                     |                     |          | -       |
| Predicted Education | -0.003              | P2                  | 0.405**  |         |
|                     | (0.162)             |                     | (14.878) |         |
| Urban               | 0.105++             | P3                  | 0.325**  | -       |
|                     | (2.808)             |                     | (27.167) | •       |
| Siblings            | 0.008               | Scale Parameter (s) | 0.621**  |         |
|                     | (1.116)             |                     | (38.055) |         |
| Future Relative     | 0. 470 <del>-</del> | Gamma Shape         | 0.160+   |         |
| Cohort Size         | (1.661)             | Parameter (α)       | (1.753)  |         |
| Past Relative       | -0.764**            |                     |          |         |
| Cohort Size         | (-3.163)            |                     |          |         |
| Trend               | -0.039++            |                     |          |         |
|                     | (19.909)            |                     |          |         |
| θ                   | 7.370++             |                     |          |         |
|                     | (14.343)            | ,                   |          |         |
| θ <sub>2</sub>      | 6.130**             |                     |          | •       |
| 2                   | (13.283)            | -                   |          | -       |
| θ                   | 4.430**             |                     |          |         |
| 2                   | (9.751)             |                     |          | -       |
| θ,                  | 2.500++             |                     |          |         |
| 4                   | (5.558)             |                     |          |         |
| Log-Likelihood      | -10548-24           |                     |          |         |
| Sample Size         | 6, 321              |                     | · · ·    | · · · · |

\*\* Significantly different from zero at the 5 percent level

. Significantly different from zero at the 10 percent level × ---

.....

| · .     |
|---------|
| · · · · |
|         |
|         |
|         |
|         |
|         |
|         |

Appendix Table 1. Ordinary Least Squares Estimates of the Education Equation. Dependent variable: years of schooling completed.

<sup>a</sup>The variable Prewar takes the value 1 if a woman was born before 1945, 0 otherwise.

b. The variable Postwar takes the value 1 if a woman was born in or after 1945, 0 otherwise.

\*\* Significantly different from zero at the 5 percent level.

Significantly different from zero at the 10 percent level.

| not Condition             | nal on Schooling. |                                       |
|---------------------------|-------------------|---------------------------------------|
| Constant                  | 4.176++           |                                       |
| (t-statistic)             | (25.623)          |                                       |
|                           |                   |                                       |
| White                     | 0.191++           |                                       |
|                           | (12.988)          | · · · · · · · · · · · · · · · · · · · |
| Father's Education        | 0.018++           |                                       |
|                           | (8.796)           |                                       |
| Motheria Education        | 0.020+-           |                                       |
| nother a Education        | (8 113)           |                                       |
|                           | (0.110)           | •                                     |
| Urban                     | 0.018             | <b>_</b>                              |
|                           | (1.348)           | 、 · · · · ·                           |
|                           |                   | ۲.                                    |
| Siblings                  | -0.014**          |                                       |
|                           | (-3.938)          |                                       |
| Future Relative           | 0.240**           |                                       |
| Cohort Size               | (2.549)           |                                       |
| Past Relative             | -0, 056           |                                       |
| Cohort Size               | (-0,604)          |                                       |
|                           |                   |                                       |
| Postvar <sup>a</sup>      | 0.032**           |                                       |
|                           | (2.189)           |                                       |
| Scale Parazeter (d)       | 0 585**           |                                       |
| DCale : al Bme Cel (V)    | (115,740)         |                                       |
| ,                         |                   |                                       |
| Gamma Shape Parameter (α) | -0.505**          | :                                     |
|                           | (-22.778)         |                                       |
| Log-Likelihood            | -8688.035         |                                       |
| Sample Size               | 10, 386           | •                                     |
| -                         | ·                 |                                       |
|                           |                   |                                       |

Appendix Table 2. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the First Birth Interval, not Conditional on Schooling.

<sup>a</sup>1 if a woman was born in 1945 or later, 0 otherwise.

\*\* Significantly different from zero at the 5 percent level

Significantly different from zero at the 10 percent level

|                           |            | • ···································· |
|---------------------------|------------|--|
| Constant                  | 5.701++    |  |
| (t-statistic)             | (7.982)    |  |
| White                     | 0.338**    |  |
|                           | (6.251)    |  |
|                           |            |  |
| Father's Education        | 0.016**    |  |
|                           | (2.075)    |  |
| Mother's Education        | -0.030**   |  |
|                           | (3, 322)   |  |
|                           |            |  |
| Urban                     | 0.151++    |  |
|                           | (2.943)    |  |
| Cibling.                  | 0.011      |  |
| STOTTUĜR                  | (1 192)    |  |
| 2                         | (1.133)    |  |
| Future Relative           | 0.796++    |  |
| Cohort Size               | (2.002)    |  |
|                           |            | · · ·                                  |
| Past Relative             | -1.044**   |  |
| Conort Size               | (-2.348)   |  |
| Postvar                   | 0.110      |  |
|                           | (0.688)    |  |
|                           |            |  |
| Trend                     | -0.051++   | • ·                                    |
|                           | (9.780)    |  |
| Scale Parameter (g)       | 1.666**    |  |
|                           | (64, 489)  |  |
|                           |            | . ·                                    |
| Gamma Shape Parameter (a) | 0.232**    |  |
|                           | (3.921)    |  |
| Log-Likelihood            | -10729.363 |  |
| <b></b>                   |            |  |
| Sample Size               | 6,321      |  |
|                           |            |  |
|                           |            | `                                      |

Appendix Table 3. Maximum Likelihood Estimates of the Extended Generalized Gamma Model for the Return to Work Model, not Conditional on Schooling.

Significantly different from zero at the 5 percent level
Significantly different from zero at the 10 percent level







Figure 2. Child Related Utility of Birth Timing and the Optimal Choice of b.



Souris 42: Hete for 1909-76 are from Department of Health and Homan Services, feational Center for Health Statistics, Vital Statistics of the United States, 1976, vol. 4; Natality (Coversment Polning Hifter, 1960), table 4 3; Soc 976 and 1938, Soon "Start Statistics, 1939," Advance Beport, Monthly Vital Statistics of the Population, 1976, and the 1939 and part formation numbers, from " States Beauty and Itality Sciences Beport, March 1988, Vital Statistics of the Population (States), p. 49, and the 1939 and part formation numbers, from " States Beauty and Itality Sciences Beport, vol. 394Heach 48, 3941), p. 4 s. Report cold botton 1939 and Ministers before States and states of a constances for the States of the States of States (States) and States States of States and States of States

Source: Russell (1982), p.2.

1

Chart. I. Live Births in the United States, 1909-10-



### Proportion of Women with no First Birth

Chart 2

Chart 3



Note: The proportions are evaluated holding background characteristics constant (at the sample means) and abstracting from trend.

#### References

Berger, Mark C., "Cohort Size and Earnings Growth of Young Workers," <u>Industrial</u> and <u>Labor Relations</u> <u>Review</u> 37, 4 (July 1984): 585-591.

Berger, Mark C., "The Effect of Cohort Size on Earnings Growth: A Reconsideration of the Evidence," <u>Journal of Political Economy</u> 93, 3 (June 1985): 561-573.

Bloom, David, "What's Happening to the Age at First Birth in the United States? A Study of Recent Cohorts," <u>Demography</u> 19, 3 (August 1982): 351-370.

Butz, William P. and Michael P. Ward, "The Emergence of Countercyclical U.S. Fertility," <u>American Economic Review</u> 69, 3 (June 1979): 318-328.

Easterlin, Richard A., <u>Population</u>, <u>Labor Force and Long Swings in Economic</u> <u>Growth</u> (New York: Columbia University Press, 1968).

Even, William E., \*Career Interruptions Following Childbirth, \* Journal of Labor Economics 5, 2 (April 1987): 255-277.

Falaris, Evangelos M. and H. Elizabeth Peters, "The Effect of the Demographic. Cycle on Schooling and Entry Wages," unpublished paper (September 1989a).

Falaris, Evangelos M. and H. Elizabeth Peters, "New Evidence on the Effect of the Demographic Cycle on the Timing of School Completion," <u>Review of</u> <u>Economics and Statistics</u> (forthcoming, 1989b).

Freeman, Richard B., "The Effect of Demographic Factors on Age-Earnings. Profiles," Journal of Human Resources 14, no.3, Summer 1979: 289-318.

Heckman, James J. and Burton Singer, "Econometric Duration Analysis," <u>Journal of</u> <u>Econometrics</u> 24 (January/February 1984): 63-132 (a).

Heckman, J. and B. Singer, "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," <u>Econometrica</u> 52, 2 (March 1984): 271-320 (b).

Lancaster, Tony, "Econometric Models for the Duration of Unemployment," Econometrica 47, 4 (July 1979); 939-956.

Lawless, J.F., <u>Statistical Methods and Models for Lifetime Data</u>, (New York: John Wiley & Sons, 1982).

Newman John L. and Charles E. McCulloch, "A Hazard Rate Approach to the Timing of Births," Econometrica 52, 4 (July 1984): 939-961.

Razin, Assaf, "Number, Spacing and Quality of Children: A Microeconomic () Viewpoint," <u>Research in Population Economics</u> 2 (1980): 279-293.

Wachter, Michael L. and William L. Wascher, "Leveling the Peaks and Troughs of the Demographic Cycle: An Application to School Enrollment Rates," <u>Review of</u> <u>Economics and Statistics</u> 66, 2 (May 1984): 208-215.