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The Third Birth in Sweden

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ABSTRACT

This paper addresses three issues in the context of analyzing transitions to third births in Sweden. First, the effects of socioeconomic variables on age specific third birth rates include the effects of such variables on the timing and spacing of the first two births. Second, the age of a woman at the time she becomes at risk of the third birth and the length of time spent waiting for the first two births may affect the transition rates to the third birth. Third, the existence of person-specific unobserved variables that account for life cycle fertility and are correlated across spells may lead to biased estimates of the parameters of socioeconomic variables affecting transition times to the third birth. Two models are considered to predict parity attainment, one neoclassical economic with a central role assigned to wages of men and women, and the other demographic that attaches importances to lagged birth durations. Neither model passes goodness of fit tests until augmented to allow for the impacts of pronatal Swedish policies that account for the observed cohort drift, in which case the neoclassical model evidences the greater promise for predicting future fertility.

A woman is at risk to have a third birth only if she has already had two births. Several important demographic consequences follow from this obvious fact. First, in order to estimate age specific third birth rates, it is necessary to account for the effect of the first two births on placing women at risk to have a third birth. The effect of socioeconomic variables on age specific third birth rates includes the effects of such variables on the timing and spacing of the first two births.

Second, even if attention focuses on the estimation of transition rates from the second birth to the third birth, it may be necessary to account for the history of a birth process up to the time a woman becomes at risk for the third birth. Parameters of transition rates may vary by parity. The age of a woman at the time she becomes at risk may affect third birth fertility. So may the length of time spent waiting for the first two births independently of any age effect.

Third, considerable evidence has accumulated that person specific unobservables are important in accounting for life cycle fertility. If such variables are correlated across spells, failure to account for them may lead to biased estimates of the parameters of socioeconomic variables affecting transition times to the third birth. The presence of such omitted variables has important implications for how we account for the history of the process in estimating transitions to the third birth. We can be much more casual about the history of a process if such variables are not present.

This paper addresses these issues in the context of analyzing third births in Sweden. Walker (1986) documents stability in the transition rates to the first and second births for the three most recent cohorts of Swedish women for which comprehensive fertility histories are available. (Women born in 1935-1939, 1940-1944 and 1945-1949.) There has been a secular decline in the transition rate to the third birth accounting for a substantial portion of the recent decline in Swedish fertility. An analysis of third births thus sheds light on an empirically important phenomenon in modern Sweden.

We estimate the determinants of third births in Sweden using longitudinal data from the Swedish fertility survey. We fit a variety of multistate duration models with time-varying covariates, general forms of duration dependence and unobservables temporally dependent across birth intervals. The variety of models estimated in our work forces us to confront the problem of model selection in multistate duration analysis. The most commonly used model selection criterion - comparing likelihoods - is inappropriate because many of our models are non-nested. We judge the fit of alternative models by using the classical chi-square goodness of fit test applied to parity attainment distributions. We also evaluate models in terms of their ability to produce parameter estimates that are stable across cohorts.

We find two strikingly different models that predict parity attainment distributions equally well. One model is consistent with neoclassical economic theory. It assigns a central role to the wages of men and women in explaining the timing and spacing of births. The other model is a purely demographic model that excludes wages and uses lagged birth durations as explanatory variables. This specification is consistent with models put forth by Rodriguez et.al (1984). Purely statistical criteria cannot distinguish between them and a model combining the regressors included in the two models fails to pass goodness of fit tests.

Because both models exhibit cohort drift, neither model is an adequate framework for forecasting the fertility of future cohorts. We argue that the neoclassical economic model augmented to allow for the impacts of pronatal Swedish policies offers a more promising vehicle for developing a framework that may account for the observed cohort drift, and that may be able to account for future fertility. The estimated cohort drift is consistent with neoclassical explanations of the impact of recent Swedish policies on fertility.

The structure of this paper is as follows. In section 1 we discuss the formulation, estimation and evaluation of multistate duration models with time varying regressors and unobservables that are correlated across spells. We note the importance of accounting for the sampling frame used to collect the data and accounting for unobservables in deriving the correct likelihood function for analyzing transition times to the third birth. We discuss the potential danger in adopting the widely used low cost "piecemeal" approach of analyzing birth spells in isolation from each other. We state conditions under which this strategy produces desireable estimates of the parameters of underlying models. We exposit a χ^2 goodness of fit test for a general multistate duration model developed in our other work and we consider model selection criteria to pick the "best" among a collection of nonnested models.

In section 2, we discuss the Swedish Fertility Survey (SFS) data analyzed in this paper. We present relevant institutional information on the Swedish economy and on Swedish natality policy. Section 3 reports the results of an extensive empirical analysis of the SFS data. Section 4 summarizes our analysis.

1. The Formulation, Estimation and Evaluation of Multistate Duration Models For The Third Birth

The third birth is the outcome of a multistate life cycle stochastic process. In making forecasts of age specific third birth rates, it is necessary to take account of the occurrence of the preceding births. Age dependent fecundity, and the hypothesis of Rodriguez et.al (1984) that outcome times of previous births affect current birth transition probabilities suggest that it may be necessary to condition on the history of a process in order to produce empirically concordant models of fertility. The more interrelated are life cycle processes and the greater the importance of age and previous durations in explaining transitions to the third birth, the more important it is to account for the occurrence and timing of prior events in predicting the occurrence and timing of third births.

The conventional demographic approach to the estimation of life cycle models is to estimate the components of life cycle processes in isolation from each other - the "piecemeal" approach. This approach is often computationally cheaper than full estimation of interrelated life cycle processes. It also enables the analyst to focus on the transitions of interest to his or her study without having to worry about other transitions of secondary concern.

If there are variables that affect outcomes that are not observed by the demographer and if they are temporally dependent across spells, the piecemeal approach is fraught with danger. Unobserved "heterogeneity" is one name given to such variables in the recent literature. Gini (1924), Sheps (1965) and Majumdar and Sheps (1974) develop models of fertility in which persistent differences among women in unobserved fecundity give rise to unobserved heterogeneity. Heckman and Walker (1987) demonstrate that it is necessary to account for such variables to produce empirically concordant models of Hutterite fertility. This section examines the dangers of the piecemeal approach when unobserved variables are part of the model specification.

We conduct our discussion within the context of a life cycle birth process. We first present the basic statistical model that underlies our empirical analysis. Some of our estimated models have time varying covariates. We state conditions for such models under which it is possible to integrate up hazards to form the survivor function in the "usual way" - i.e., as is done in models without time varying covariates. We then discuss the specification of multistate models of fertility and demonstrates how unobservables naturally arise in such models. For the specification of unobservables universally adopted in the empirical literature, we discuss the danger of the piecemeal approach in estimating component transitions of a model. We present our strategy for estimating multistate duration models with time varying variables, unobservables, censoring and lagged durations. We conclude Section 1 with a discussion of methods for evaluating alternative models.

1.1 A Birth Process

We assume that a woman's birth history evolves in the following way. The woman becomes at risk for the first birth at calendar time $\tau = 0$. This is the age of menarche. We define a finite-state continuous time birth process $\{Y(\tau), \tau > 0\}$, $Y(\tau) \in C$, where the set of possible states (parities) is finite ($C = \{0,1,2,\ldots,\bar{C}\}$, $\bar{C} < \infty$). An element of C defines parity attained at time τ. Let $R = k$, $k \in C$, denote the parity attained by the woman ($Y(\tau)$) at the kth transition time. Transitions occur on or after $\tau = 0$.

The basic building block for multistate duration models is the conditional hazard. Define $H(\tau)$ as the relevant conditioning set at time τ. The choice of the variables to include in the relevant conditioning set involves matters of judgement and context. For the moment, we assume that these are known. $H(\tau)$ may include variables which influence the woman's transition to the next birth.

Anticipations about the future formed at time τ that affect transitions may be part of the $H(\tau)$. So may be the relevant past including the history of the process up to time τ (previous birth intervals, etc.).

For simplicity we assume that all random durations $T_1, \ldots, T_{\bar{C}}$ are absolutely continuous random variables. This means that we assume that each random variable can be described by a density which integrates to a distribution function. If a woman becomes at risk for the j^{th} birth at time $\tau(j-1)$, the conditional hazard at duration t_j is defined to be

(1) $$h_j(t_j|H(\tau(j-1) + t_j)).$$

Under conditions specified in Yashin and Arjas (1988), we may integrate (1) to form the survivor function

$$S(t_j|H(\tau(j-1) + t_j)) = \exp - \int_o^{t_j} h_j(u|H(\tau(j-1) + u))du.$$

Note that the information contained in $H(\tau(j-1) + t_j)$ potentially includes all the information for values of durations less than t_j. For absolutely continuous T_j their condition requires that

(2) $$\Pr(T_j \leq t_j|H(\tau(j-1) + t_j)) = \Pr(T_j \leq t_j|H(\infty))$$

where $H(\infty)$ is the information set assumed to be available at all future times. This condition states that the information available at time $\tau(j-1) + t_j$ fully characterizes the conditional distribution of T_j i.e., that new information arriving after time $\tau(j-1) + t_j$ does not help in predicting the probability that $T_j \leq t_j$. Note that this condition does not exclude from H variables that are realized after time $\tau(j-1) + t_j$ that are perfectly forecastable at that time (e.g, age one period in the future).

Assuming that condition (2) holds we may describe the birth process of a woman by the following recipe. A woman begins menarche at parity zero so $Y(0) = R = 0$, and continues childless a random length of time, governed by the survivor function

$$(3) \qquad \Pr(T_1 > t_1 | H(\tau(0) + t_1)) = \exp\left[- \int_o^{t_1} h_1(u | H(\tau(0) + u) du \right].$$

At calendar time $T(1) = \tau(1)$, the woman conceives and moves to the state $R = 1$. The woman resides in state 1 for a random length of time T_2 governed by the conditional survivor function

$$(4) \qquad \Pr(T_2 > t_2 | H(\tau(1) + t_2)) = \exp\left[- \int_o^{t_2} h_2(u | H(\tau(1) + u)) du \right].$$

By construction, $T_2 = T(2) - T(1)$. At transition time $T(2) = \tau(2)$, the woman conceives again and moves to parity $R = 2$.

In the general case, we have $Y(\tau) = R$ for $\tau(k) \le \tau \le \tau(k+1)$. Now $T_k = T(k) - T(k-1)$ is governed by the conditional survivor function

$$(5) \qquad \Pr(T_k > t_k | H(\tau(k-1) + t_k)) = \exp\left[- \int_o^{t_k} h_k(u | H(\tau(1) + u)) du \right].$$

The conditional density function of duration $T_k = t_k$ is

$$(6) \qquad g(t_k | H(\tau(k-1) + t_k) = h_k(t_k | H(\tau(k-1) + t_k)) \cdot S(t_k | H(\tau(k-1) + t_k)).$$

Assuming conditional independence, the conditional joint density of

$(T_1, T_2, \ldots, T_{\bar{C}})$ given $H(\tau(0) + \sum_{i=1}^{\bar{C}} t_i)$ is

$$(7)\quad g(t_1,\ldots,t_{\bar{C}}|H(\tau(0) + \sum_{i=1}^{\bar{C}} t_i)) = \prod_{k=1}^{\bar{C}} h_k(t_k|H(\tau(k-1) + t_k)) \cdot S(t_k|H(\tau(k-1) + t_k)).$$

If $H(\tau(j-1))$ includes all lagged durations and contains all relevant conditioning information, then conditional independence is a consequence of the laws of conditional probability.

1.2. Specifying A Model of Demographic Interest: The Relevant Conditioning Set and The Role of Unobserved Heterogeneity

It is natural, and for certain purposes, desireable, to equate the relevant conditioning set $H(\tau)$ with the available covariates. An analysis of the relationships between observed covariates and fertility outcomes is the obvious point of departure for any descriptive study of fertility.

The limitations of such empirical relations are well known. It is often the case that analysts and their readers can think of many omitted variables not in the available covariate set that plausibly affect fertility. The included variables may proxy the omitted variables. Estimated effects of included variables on fertility are inclusive of the effect of the included variables in their own right on fertility and their ability to proxy the omitted variables. These issues are of paramount interest when we wish to use fitted models to evaluate policy interventions which change included variables but not omitted variables. Fitted empirical models may shed little light on the likely effect of such policy interventions.

These issues are central in the analysis of fertility. A long-standing demographic tradition starting with Gini (1924) and continuing with Brass (1958), Sheps (1965), Sheps and Menken (1973) and Menken (1975) postulates temporally persistent female fecundity as an important determinant of fertility.

Temporally persistent fecundity differences among women explain declining spell specific hazards that are a universal feature of fertility data. Despite much careful work (see, e.g. Bongaarts and Potter (1983)), it is difficult to obtain good measures of fecundity. In most data sets on fertility, there are no measures at all.

The empirical importance of accounting for unobserved fecundity is illustrated in our recent work with Hotz (Heckman, Hotz and Walker, 1985). Models that do not account for unobserved fecundity produce the "engine of fertility" story of Rodriguez et. al (1984): early first births "cause" subsequent fertility. Accounting for unobservables, we found that the engine either shuts down or runs in reverse, at least in Swedish data. The Rodriguez et. al policy conclusion about the importance of preventing teenage pregnancy equates a fitted empirical relationship with a valid behavioral relationship. For policy and interpretive analysis, it is sometimes not valid to equate $H(\tau)$ with the available conditioning variables.

It is analytically clarifying to distinguish two different types of unobservables: (a) those that are known to the woman being studied and affect her behavior but are not known to the observing demographer and (b) those that are not known to either the woman being studied or the observer. The latter type of unobservables produce dynamics of their own if the agents being studied learn about their unobservables over the life cycle. It is necessary to account for both types of unobservables to recover the parameters relevant for policy or intervention analysis. We start our discussion with the first case.

The study of unobservables in multistate duration models is still in its infancy. The few papers that fit models with unobservables universally assume that unobservables, denoted by $\Theta(\tau)$, can be summarized by a scalar random variable Θ which is time-invariant with distribution $M(\theta)$. Θ is assumed independent of $H(0)$, the initial state of the process. (See, however, Heckman and Singer, 1985). The conventional model with unobservables augments (6) so that densities are defined conditional on $H(\tau)$ and θ:

(6)′ $$g(t_k|H(\tau(k-1) + t_k),\theta) = h_k(t_k|H(\tau(k-1) + t_k)\theta)S(t_k|H(\tau(k-1) + t_k),\theta).$$

The conditional density of $T_1,\ldots,T_{\bar{C}}$ given $H(\tau(0) + \sum_{i=1}^{\bar{C}} t_i)$ is

(7)′ $$g(t_1,\ldots,t_{\bar{C}}|H(\tau(0) + \sum_{i=1}^{\bar{C}} t_i)) = \int_{\underline{\Theta}} \prod_{i=1}^{\bar{C}} g(t_k|H(\tau(k-1) + t_k),\theta)dm(\theta)$$

where $\underline{\Theta}$ is the support of Θ i.e. its domain of definition.

The two key assumptions in the recent literature - (a) that $\Theta(\tau)$ is time invariant ($= \Theta$) and (b) that Θ is independent of $H(0)$ - are both controversial because it is easy to think of cases where they are false. Assumption (a) underlies the classical demographic model of fecundity of Gini (1924), Brass (1958), Sheps (1965), Sheps and Menken (1973) and Menken (1975).

Unobservables unknown to the agent being studied may still be relevant components of model specification. In a study of fertility, it is implausible that individuals know their own θ, at least in making decisions about their first birth. Nonetheless, accounting for θ is often necessary in order to produce estimates that isolate genuine behavioral effects of covariates on fertility. The existence of unobservables unknown to the woman and the demographer provides a motivation and interpretation for the presence of statistically significant lagged birth intervals in fitted hazard rates for birth parities beyond the first.

A simple example makes this point concrete. Suppose that women consciously affect their birth probabilities by practicing contraception. Let the hazard rate for the j^{th} birth be

$$(8) \qquad h_j(t_j | H(\tau(j-1) + t_j), \theta) = c_j(x_j)\theta, \qquad H(\tau(j-1) + t_j) = x_j,$$

where c_j is a contraceptive choice component determined by the woman's behavior as a function of <u>her</u> information x_j and θ is a fecundity component. For parity $j = 0$, it is unreasonable to assume that a woman knows θ. For parity $j > 0$, she may estimate it from her own fertility experience. Specification (8) assumes that fertility densities conditional on x_j and θ are exponential. Heckman and Walker (1989) find that conditional exponentiality as assumed in this example is a valid description of Hutterite time to first conception data. The relevant conditioning set includes more information than the woman being studied has at her disposal.

Hazard (8) implies that the conditional density of duration T_j is

$$g_j(t_j | H(\tau(j-1) + t_j), \theta) = \theta c_j(x_j) \exp(- t_j c_j(x_j)\theta).$$

The goal of policy and interpretive analysis is to recover $c_j(x_j)$ in the presence of θ. To keep the example simple we assume that the demographer knows x_j. In fact, he may not and there may be an additional source of unobservables arising from components of x_j known to the agent but not to the observing demographer. This is the kind of unobservable already discussed.

Assuming that the density of Θ exists and is $m(\theta)$ and that Θ is independent of X_1, we may write the density of the first spell duration condition on $X_1 = x_1$ as

$$g_1(t_1 | x_1) = c_1(x_1) \int_{\underline{\Theta}} \theta \, e^{-t_1 \theta c_1(x_1)} m(\theta) d\theta.$$

From the analysis of Elbers and Ridder (1982), we know that if $E(\Theta) < \infty$, $c_1(x_1)$

and the distribution $M(\theta)$ can be identified from duration data even if the functional form of c_1 is not known. Failure to control for θ produces estimated negative duration dependence.

Women who experience a first birth learn something about their θ, and this information <u>might</u> enter <u>their</u> information set and affect contraceptive decisions for the second birth. If women know $m(\theta)$, by Bayes theorem

$$(9) \qquad m(\theta|t_1,x_1) = \frac{m(\theta)g_1(t_1|x_1,\theta)}{g_1(t_1|x_1)}$$

is their revised estimate of the density of Θ. Duration t_1 is in the woman's information set for making decisions about c_2. So is $m(\theta|t_1,x_1)$. Variable t_1 may or may not enter x_2 in $c_2 = c_2(x_2)$. If t_1 is the only new information acquired after one birth, then $x_2 = (x_1,t_1)$ and $c_2 = c_2(x_1,t_1)$. For simplicity we assume that this is the case.

The density for t_2 given x_1 and t_1 is then

$$(10) \qquad g_2(t_2|t_1,x_1) = \int_{\underline{\Theta}} g_2(t_2|t_1,x_1,\theta)m(\theta|t_1,x_1)d\theta$$

$$= c_2(x_1,t_1) \int_{\underline{\Theta}} \theta \, e^{-t_2\theta c_2(x_1,t_1)} m(\theta|t_1,x_1)d\theta$$

$$= c_1(x_1) \frac{c_2(x_1,t_1)}{g_1(t_1,x_1)} \int_{\underline{\Theta}} \theta^2 e^{-\theta[t_1c_1(x_1)+t_2c_2(x_1,t_1)]} m(\theta)d\theta .$$

The piecemeal empirical approach which estimates the hazard associated with $g_2(t_2|t_1,x_1)$ without accounting for Θ cannot isolate the effect of x_1 on c_2. It does not distinguish the effect of t_1 on contraceptive choice in the second interval from the effect of t_1 on the conditional distribution of Θ. The latter effect is only a compositional effect which arises because women with shorter t_1 have on average a higher value of Θ. In order to determine if t_1

enters c_2 it is necessary to decompose (10) into its constituent components on the right hand side.[1] The mathematics that informs us that

$$g(t_1,t_2|x_1) = g_2(t_2|t_1,x_1)g_1(t_1|x_1) = \int_{\underline{\Theta}} g_2(t_2|t_1,x_1,\theta)g_1(t_1|x_1,\theta)m(\theta)d\theta$$

does not justify basing policy statements on hazards estimated for the two conditional densities in the middle term of the expression.

To finish this example, note that (9) is still true whether or not the women being studied are Bayesian learners. Values of t_1 convey information on Θ which the women may or may not use. Even if they are not Bayesians, t_1 may enter their decision sets because it may affect their resources, states of mind or reproductive capacities. Note further than in formulating the correct likelihood for the model using the recent approach it is not necessary to assume that Θ is independent of the regressors. Obviously T_1 is not independent of Θ. The only requirement is that Θ is independent of $H(0) = (X_1)$. Note finally that the appropriate density against which to integrate $g(t_2|t_1,x_1,\theta)$ to produce $g(t_2|t_1,x_1)$ is $m(\theta|t_1,x_1)$ not $m(\theta)$.

1.3 Dangers of The Piecemeal Approach

For the specification of heterogeneity used in the recent literature - Θ a time invariant component distributed independently of $H(0)$ - we consider the following question. When can one safely ignore (not estimate) the lower parity hazard rates and still consistently estimate policy relevant hazard rates for parities beyond the first? To avoid triviality, we assume that the parameters of the lower parity hazard rates are not known. Piecemeal estimation strategies that analyze one transition in isolation from other transitions are appealling

[1] Honore (1987) establishes that c_1 and c_2 can be nonparametrically identified without any restriction on $E(\Theta)^2$.

because they are cheap to implement. Yet, in the presence of unobservables, this strategy generally produces inconsistent estimates of the policy relevant parameters as our example showed in the previous subsection.

We assume knowledge of the complete history of the process up to the survey date for each woman in our sample. Thus we abstract from biased sampling problems and initial conditions problems that are discussed in Heckman and Singer (1985), Hoem (1985) and Sheps and Menken (1973). We establish the following theorem.

Theorem: Under the stated <u>sufficient</u> conditions (beyond the assumptions previously made about heterogeneity), the piecemeal strategy produces consistent parameter estimates for third birth transitions:

(I) $H(0) = H(\tau)$, all τ

(*i.e.* the covariates are time invariant)

(II) The distributions of T_1 and T_2 given $H(0)$ are nondefective

(so $\lim_{t_j \to \infty} S(t_j|H(0)) = 0$, $j = 1,2$)

(III) There is no censoring. ■

Proof:

The joint density of T_1, T_2, T_3 is

$$g(t_1,t_2,t_3|H(0)) = \int_{\underline{\Theta}} g_1(t_1|H(0),\theta)g_2(t_2|H(0),\theta)g_3(t_3|H(0),\theta)d\mu(\theta)$$

Integrating out t_1 and t_2, we obtain

$$g_3(t_3|H(0)) = \int_{\underline{\Theta}} g_3(t_3|H(0),\theta)d\mu(\theta) .$$

Valid inference can be made about the third spell using only data on the third spell. ■

These conditions are rather severe. Assumptions (II) and (III) imply that we observe all transition times for all women. Assumption (II) implies that all women eventually give birth - i.e there is no sterility or stopping behaviour. (I) rules out time dependent environmental or developmental covariates. It also rules out lags affecting behavior as is assumed in Rodriguez et.al (1984).

These conditions ensure that all women are at risk to have a third birth. The implicit sampling frame is assumed to be of sufficient length to ensure that we observe all first and second spells for all women. Thus the distribution of Θ for women at risk for the first birth is the same as the distribution of women at risk for the third birth. Since the relevant conditioning set does not change with parity ($H(\tau) = H(0)$ for all τ), the conditioning set for the third birth is independent of Θ. There is thus no selective attrition of women from the sample and there is no spurious feedback from Θ to variables in the conditioning set because the conditioning set is fixed and independent of Θ. This rules out any learning by women or any other feedback from previous outcomes to current decisions.

Bayes' theorem reveals that information about t_1 and t_2 gives information about Θ. Thus for density $m(\theta)$,

$$(11) \qquad m(\theta|t_1,t_2,H(0)) = \frac{m(\theta)g_1(t_1|H(\theta),\theta)g_2(t_2|H(0),\theta)}{\int_{\underline{\Theta}} g_1(t_1|H(0),\theta)g_2(t_2|H(0),\theta)dm(\theta)} .$$

As previously noted in subsection (1.2) agents might utilize information about lagged birth intervals in making estimates of Θ and decisions about third births. Then the information set $H(\tau(2))$ would depend on t_1 and t_2 and assumption (I) would be false. If Θ were known to the agent but not to the observing statistician, there would be no such learning, so (I) might still be true.

An instructive alternative derivation of our Theorem starts with (11) and $g_3(t_3|H(0),\theta)$ and derives the marginal distribution of T_3 by integrating out t_1 and t_2. Thus

(12) $$g_3(t_3|H(0))$$

$$= \int_0^\infty \int_0^\infty \int_{\underline{\Theta}} g_3(t_3|H(0),\theta)m(\theta|t_1,t_2,H(0))g(t_1,t_2|H(0))d\theta dt_1 dt_2$$

$$= \int_{\underline{\Theta}} g_3(t_3|H(0),\theta)m(\theta)d\theta.$$

Note that we use the fact that the denominator of (11) is $g(t_1,t_2|H(0))$.

As long as the relevant third birth conditioning set $H(\tau) = H(0)$ for all τ, and the limits of integration for t_1 and t_2 are between 0 and ∞, the durations of previous spells and their distributions are irrelevant for constructing the density for the third birth.

The theorem fails if these conditions are not satisfied. Thus if $H(\tau) \neq H(0)$ in the third birth conditioning set, t_1 and t_2 enter the conditioning set of $g_3(t_3|H(\tau(2)),\theta)$ since $\tau(2) = \tau(0) + t_1 + t_2$. The problem no longer separates and the integration includes the conditioning arguments. If the data are censored so $t_1 + t_2 + t_3 \leq c$, then the argument breaks down because the distributions of the first two spells enter the construction of the marginal density of t_3. If the conditional distributions of T_1 and T_2 are defective then the third line in equation (12) no longer holds and instead becomes

$$\int_{\underline{\Theta}} g_3(t_3|H(0),\theta) \left[\int_0^\infty\int_0^\infty g_2(t_2|H(0),\theta)g_1(t_1|H(0),\theta)dt,dt_2\right]dm(\theta)$$

where the term in square brackets does not equal 1 and in general depends on the parameters of g_2 and g_1.

We now make these observations somewhat more precise.

A. Defective Distributions

If the densities of either t_1 and t_2 are defective and either

$$\int_0^\infty g_1(t_1|H(0),\theta)dt_1 = K_1(H(0),\theta)$$

or

$$\int_0^\infty g_2(t_2|H(0),\theta)dt_2 = K_2(X,\theta)$$

depends on θ, then

$$\int g(t_1,t_2,t_3|H(0))dt_1dt_2 = \int_{\underline{\Theta}} K_1(H(0),\theta)K_2(H(0),\theta)g_3(t_3|H(0),\theta)d\mu(\theta)$$

and the parameters of the K_i functions fundamentally enter the construction of the marginal density of T_3.[2]

In the absence of θ in the first two densities, and in the absence of any restrictions connecting the parameters of g_3 with those of g_1 and g_2, the model separates and factors $K_1(H(0))$ and $K_2(H(0))$ can be ignored in obtaining consistent estimates of the parameters of g_3 using maximum likelihood.

B. Censoring

If the observations are censored so $t_1 + t_2 + t_3 \le c$, then integrating out t_1 and t_2 in the joint density produces

$$\int_0^{c-t_3} \int_0^{c-t_2-t_3} g(t_1,\ t_2,\ t_3|H(0))dt_1dt_2$$
$$= \int_{\underline{\Theta}} G_1(c-t_2-t_3|H(0),\theta)G_2(c-t_3|H(0),\theta)g_3(t_3|H(0),t,\theta)m(\theta)d\theta$$

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2 The interchange of integrals is justified by Tonelli's theorem.

where G_i is the cdf of T_i. As in the defective case, the analyst must take account of the parameters of previous spell densities in analyzing third spell data. Now, however, even if θ does not appear in G_1 and G_2, and there are no parameter restrictions connecting G_3 with G_1 and G_2, account must be taken of the first two spell densities in constructing the correct likelihood for the marginal third spell.

C. Time Dependent Conditioning Sets

If attention focuses on estimating $g_3(t_3|H(\tau(2) + t_3),\theta)$ and if $H(\tau(2))$ is a non-trivial function of $\tau(2)$ (so $\tau(2)$ determines the conditioning set for the third spell) and if θ determines g_1 and/or g_2, an additional complication, first noted by Chamberlain (1985), precludes conditioning on $H(\tau(2) + t_3)$ in constructing the marginal third spell density without adjusting for the effect of the past history on the distribution of Θ. The conditioning set in this case is determined by the outcomes of the preceding spells which depend, in part, on Θ. The marginal density of Θ conditional on $H(\tau(2))$

$$m(\theta|H(\tau(2)) \tag{13}$$

is not the same as the marginal population density of θ, $m(\theta)$. The third spell density is

$$\begin{aligned} &g_3(t_3|H(\tau(2) + t_3)) \\ &\quad = \int g_3(t_3|H(\tau(2) + t_3),\theta)m(\theta|H(\tau(2))d\theta. \end{aligned} \tag{14}$$

By Bayes' theorem,

$$m(\theta|H(\tau(2)) = \frac{m(\theta)g_1(t_1|H(\tau_0+t_1),\theta)\ g_2(t_2|H(\tau(0)+t_2),\theta)}{\int_{\Theta} g_1(t_1|H(\tau_0+t_1),\theta)g_2(t_2|H(\tau_0+t_1+t_2),\theta)dm(\theta)d\theta}$$

where $\tau(2) = \tau(0) + t_1 + t_2$. The parameters of g_1 and g_2 enter the construction of the marginal third spell distribution in a fundamental way. Provided that interest centers on estimating $g_3(t_3|H(\tau(2) + t_3),\theta)$, one must account for the influence of the preceding spells on the sampled distribution.

A consistent alternative estimation strategy to the piecemeal approach is to estimate the model recursively i.e. estimate the parameters of g_1 from data on T_1, then fixing those parameters, form the correct marginal density of T_2, etc. Provided that the first stage estimators are consistent and estimation error is accounted for in computing standard errors, one can use the constructed marginal density accounting for dependence on the past to estimate the parameters of g_3. In unpublished work, Heckman, Hotz and Walker have implemented this strategy with mixed success.[3]

1.4 Empirical Specification

In this paper, we approximate the j^{th} conditional hazard using the following functional form:

$$(15) \qquad h_j(t_j|H(\tau(j-1) + t_j),\theta) = \exp\left\{ \gamma_{oj} + \sum_{k=1}^{K} \gamma_{kj} \left[\frac{t^{\lambda_{kj}} - 1}{\lambda_{kj}}\right] + \underset{\sim}{Z}(t)\beta_j + c_j\theta \right\}$$

where $\underset{\sim}{Z}(t)$ includes all observed (by the demographer) covariates possibly including durations from previous spells. Parity dependence is incorporated by allowing coefficients to bear parity specific subscripts.

There are several reasons for incorporating duration dependence into the hazard even given θ. The waiting time from the onset of menstruation to first

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3 Note however that stronger identifiability conditions are required to implement this piecemeal recursive approach than if joint estimation is performed. Honore (1987) demonstrates how access to multiple spells of data on the same person weakens the identifiability requirements that must be imposed

conception and the higher order waiting times are convolutions of underlying component distributions.[4] A conception is followed by a gestation period which is followed by a period of postpartum amenorrhea before the transition to the first conception. The time to first birth is a convolution of time from menarche to exposure of pregnancy (marriage or cohabitation) and the waiting time to pregnancy given exposure. Positive duration dependence is produced when the component processes are exponential.

Hazard specification (15) encompasses a variety of widely used models. Setting $\underset{\sim}{\beta} = 0$, $K = 1$, and $c_j = 0$, (15) specializes to a Weibull model if $\lambda_{1j} = 0$, to a Gompertz hazard if $\lambda_{1j} = 1$, and to a quadratic model if $K = 2$ and $\lambda_{1j} = 1$ and $\lambda_{2j} = 2$. An exponential model is produced if $K = 0$. Because many conventional duration models are nested within this framework, it is often possible to use likelihood ratio procedures to test competing specifications. Specification (15) also extends previous models by allowing for general time-varying covariates and by introducing unobserved heterogeneity component θ that is correlated across spells. Permitting the c_j to vary by parity allows the scalar unobservable to play a different role in different transition densities.

In our empirical work, we estimate distribution $M(\theta)$ by the nonparametric maximum likelihood (NPMLE) procedure described in Heckman and Singer (1984). This procedure approximates any distribution function of unobservables with a finite mixture distribution. Thus we estimate

$$\{p_i, \theta_i\}_{i=1}^{I}$$

where p_i is the weight placed on θ_i, the θ_i are ordered from lowest to

to identify single spell models.

4 We assume the components are independently distributed.

highest and $\sum_{i=1}^{I} p_i = 1$. I is estimated along with the other parameters of the model. Under conditions specified in Heckman and Singer (1984), the estimated empirical distribution function converges in distribution to $M(\theta)$ at all points of continuity of the latter as the sample size increases. It is the likelihood maximizing approximation to the true distribution.

A useful feature of the Heckman-Singer (1984) NPMLE is that it allows for the possibility of point mass at $\theta = -\infty$. For the transition to the first birth, such a value of θ implies (for $c_1 > 0$) that the proportion of the population having this value is the proportion having no births. A value of $\theta = -\infty$ sets hazard (15) to zero and captures permanent biological or behavioral sterility. In Heckman and Walker (1987a) we extend this feature of the NPMLE to a multi-state setting and allow for stopping behavior at all birth parities.

The survivor function utilized in our empirical work is based on hazard (15). The survivor function for the j^{th} birth is

$$S_j(t_j | \underset{\sim}{Z}(t), \theta) = P^{(j-1)} + \tag{16}$$
$$(1-P^{(j-1)}) \exp\left\{- \int_0^{t_j} h_j(u|\underset{\sim}{Z}(t), \theta)du\right\}, \quad j = 1,\ldots,C,$$

where $P^{(j-1)} = \Pr(\theta = -\infty)$. The proportion of those at risk for a j^{th} birth who never attain parity j, given θ, is

$$\lim_{t\to\infty} S_j(t | \underset{\sim}{Z}(t), \theta) = P^{(j-1)} +$$
$$+ (1-P^{(j-1)}) \exp\left\{- \int_0^{\infty} h_j(u|\underset{\sim}{Z}(t), \theta)du\right\}.$$

Although it is in principle possible to parameterize $P^{(j-1)}$ to depend on regressors (see Heckman and Walker (1987a)), we do not do so in this paper.

Collecting all of these ingredients, the contribution to sample likelihood of a woman with fertility history $T_1 = t_1$, $T_2 = t_2$, $T_k = t_k$ sampled with an incomplete $k+1^{st}$ spell exceeding $\bar{t}_{k+1}$ is

$$\sum_{i=1}^{I} \prod_{j=1}^{k} \left[\frac{-\partial \ln S_j(t_j | \underset{\sim}{Z}(t), \theta_i)}{\partial t_j} \right] S_j(t_j | \underset{\sim}{Z}(t), \theta_i) S_{k+1}(\bar{t}_{k+1} | \underset{\sim}{Z}(t), \theta_i) p_i$$

using hazard (15) to form survivor (16). We estimate the parameters $\underset{\sim}{\omega}_j = (\gamma_{oj}, \gamma_{kj}\ (k = 1,\ldots,K), \underset{\sim}{\beta}, c_j, p_i, \theta_i, I)$, $j = 1,\ldots,C$. We normalize $c_1 = 1$ and observe that for $j = 1$, $\tilde{P}^{(0)} = \Pr(\Theta = -\infty)$. Estimated model parameters are consistent under conditions specified in Heckman and Singer (1984) and Honore (1987). A general multistate computer program, CTM, is used to estimate the model. (See Yi et.al (1987) and Heckman and Walker (1987a)).

1.5 Model Selection Criteria

Hazard (15) produces a variety of models. How should one select among alternative models? Conventional statistical model selection procedures based on ranking models by their likelihood values require that all competing specifications be nested versions of a general model. Classical likelihood ratio tests cannot be used to select among non-nested models. Many plausible candidate models generated by hazard (15) are not nested. For example, a quadratic hazard models ($K = 2$, $\lambda_{1j} = 1$, $\lambda_{2j} = 2$) and a Weibull model ($K = 1$, $\lambda_{1j} = 0$) are not nested.

Unfortunately, little is known about nonnested model selection. What is known is that ranking nonnested models on the basis of likelihood values rewards complex models with many parameters which may do very poorly when measured by predictive criterion such as out-of-sample forecasts. Based on this observation, several procedures have been advocated in the recent literature. Schwarz (1978) presents a large sample model-selection criterion for selecting a best member of an exponential model that penalizes models with many parameters.

His procedure is not applicable here because hazard (15) generates models outside the exponential family. The Cox (1962) procedure for choosing among non-nested models is not appropriate for the problem at hand either because it focuses on the problem of choosing between two model specifications and not on the problem of selecting a true model out of a large set of candidate models. A variety of other procedures have been proposed using various metrics of model fit. There is no agreement about a best procedure.

An ad hoc model selection criterion uses computational cost or computational complexity as the metric by which to evaluate competing model specifications, ignoring fit altogether. This criterion is more often applied across studies than within a given study. Judgements about computational complexity are based on the availability of computing resources as well as on previous computing experience. It is a myopic criterion in light of the steady advance of computing power.

In this paper, we use χ^2 goodness of fit tests to examine how well alternative models fit the data. The χ^2 test can be defended as a conventional and well-understood metric that provides cell-by-cell information about the empirical success or failure of any candidate specification. Moreover under our conditions on the covariates, it is well known that in large samples the true model is the best fitting one provided that proper account is taken of the effect of parameter estimation on the distribution of χ^2. Using each of our fitted models, we predict the expected number of conceptions for each woman with exposure to pregnancy of time τ. By evaluating alternative models by their ability to predict births at a given exposure, we use a different dependent variable (counts or parity) than is used to fit the model (durations). In a parametric model that does not fully saturate the data, this evaluation strategy is a much more stringent test of competing models than would be obtained by using the same dependent variable both to fit and evaluate competing specifications of the underlying stochastic process.

The predictive χ^2 tests measure the discrepancy between predicted and sample parity distributions for a fixed exposure interval τ. To define the test statistic, let $\hat{P}_j(\tau)$ denote the predicted proportion at parity j (j=0,1,2,3) by exposure length τ; let $P_j(\tau)$ denote its observed sample counterpart. The test statistic is

$$R(\tau) = N \sum_{j=0}^{3} \frac{(\hat{P}_j(\tau) - P_j(\tau))^2}{\hat{P}_j(\tau)}$$

where N is the sample size. Under conditions specified in Heckman (1984), $R(\tau)$ has an asymptotic χ^2 distribution with three degrees of freedom. Single cell tests are asymptotically distributed as χ^2 with one degree of freedom. Determination of the predicted parity distribution ($\hat{P}_j(\tau)$, j=0,...,3) requires the evaluation of multidimensional integrals for each woman in the sample. In Heckman and Walker (1987a) we describe a Monte Carlo integration procedure to determine the predicted parity distribution. Because the predicted parity distribution depends on estimated parameters, we should adjust the test statistics to account for parameter estimation error. Computational costs required to produce numerically stable versions of the estimation-error adjusted test proved to be prohibitive. All of the χ^2 statistics reported in Section 3 do not adjust for parameter estimation error in the fashion described in Heckman and Walker (1987b). Using the same data to estimate and test the model biases the conventional χ^2 test towards acceptance (Heckman 1984). Our experience in simpler models suggests, however, that correcting our test statistics for estimation error will not reverse the inference reported in Section 3.[5] Similar

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[5] An alternative procedure splits the original sample into estimation and testing samples. This procedure avoids the bias towards acceptance induced by using the same data to estimate and test a model. In fact, the χ^2 test for the

findings reported by Heckman and Sedlacek (1985) and Feinstone (1984).

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split sample test is biased towards rejection. When this procedure is applied to the data analyzed in Section 3 we find no reversal of inference from the χ^2 tests which do not account for estimation error.

2.0 The 1981 Swedish Fertility Survey and Institutional Background

In this section we describe the data we analyze. We then present recent policy and demographic trends in Sweden. This discussion provides context for interpreting the empirical analysis presented in the next section.

2.1 The 1981 Swedish Fertility Survey

The data used in this study are from the 1981 Swedish Fertility Survey. It is a retrospective survey conducted by Statistics Sweden of native born Swedish women from the birth cohorts 1936-60. Women are drawn from the Central Population Register by a random sample from five five-year birth cohorts (1936-40,1941-45,...,1956-60). The survey instrument administered was a World Fertility questionaire modified to fit the Swedish context. It contains over 100 questions on life cycle fertility, employment, education, marital and cohabitational (consensual unions) events as well as social background, current life style and future fertility plans. The quality of the survey data is generally considered to be good. (See Hoem and Rennermalm (1985).) The number of cases analyzed in this paper and the distribution of births for the first four cohorts (1936-55) are reported in Table 1. Less than a third of the members of the youngest cohort (1956-60) have a first birth and accordingly data from this cohort are not analyzed. We include the fourth cohort in our analysis even though it contains few third births.

The survey did not gather individual wage and income information. To circumvent this problem two time series on wages and income were constructed. The first series uses the real average annual manufacturing male and female wage rates to proxy male income and female wages. Wilkinson (1973) uses these wages in his study of Swedish fertility. The manufacturing wage series is the only gender-specific wage series available from published sources for the entire period under consideration (1948-81). We also constructed a time series of wages using summary measures of personal tax returns by age and sex for selected years published by Statistics Sweden. Using a modest amount of interpolation it is possible to generate a complete age and gender specific income series.

2.2 Institutional Background and Recent Demographic and Economic Trends

During the post-war period the trend of the female-male wage ratio in Sweden has been very different than its counterpart in the U.S. Real wages in Sweden increased during the post-war period. Over the period 1950-1980 the manufacturing sector real male wages increased 96% while real female wages rose 120%. Most of the gain occurred before 1977. Figure 1 plots the female wage as a percent of the male wage for manufacturing wages. By 1980, female wages were 90% of male wages. In contrast, over the same period in the U.S., female wages as a percent of male wages remained roughly constant at 65%. To the extent that child care is a female-time intensive activity, an exogeneously imposed narrowing of wages should lead to a reduction of fertility if the neoclassical economic theory of fertility is correct.

It is plausible that in Sweden the wage process is exogenous to the fertility process. Sweden uses centralized collective bargaining agreements to set wages and salaries. From the mid-1950's until 1983 industrial wages have been set by collective bargaining agreements between the national trade union and the national employers association. A basic principle of the national collective bargaining agreements which reflects Swedish egalitarian beliefs is the "solidaristic wage policy". Developed by the national trade union, it became part of the national agreement in the late 1950's. The essence of wage solidarity is "equal pay for equal work - workers performing the same job are expected to receive the same wage, irrespective of interfirm or interindustry differences in productivity and profitablity" (Flanagan (1986)). Operationally, this has meant increasing the wage of low productivity workers (primarily women) while moderating wages increases for of high productivity workers in profitable industries.

The implementation of the solidaristic wage policy into national collective bargaining agreements accounts for the increasing relative wage rates of women in Sweden. Note in Figure 1 that the gain in relative female wages occurs after 1960. Bjorklund (1986) and Flanagan (1986) argue that the solidaristic wage policy has been effective in compressing all aspects of the wage structure (e.g. age, experience, gender, education and industry differentials) since the mid-1960's. These studies have two important implications for the empirical work presented in this paper. First, they imply that the change in relative female wages was due to an exogenous, institutional, force. Second, they lend credibility to our use of aggregate wages in an analysis of individual fertility histories since aggregate wage policy uniformly applied accounts for much of the wage growth of individuals.

In addition to the changing relative wage trend since the Second World War, Sweden has actively legislated a broad range of social policies. For example, Sweden has been at the forefront of providing child care benefits to allow women equal opportunity in the labor market. Since the 1970's these programs have been explicitly worked-conditioned with benefits replacing labor earnings for a considerable period of time following the birth of a child. The child benefit programs apply to women in all parities considered in this paper. An important feature of Sweden's other social programs is that with few exceptions, they are not means-tested.

Concurrent with the increasing level of real wages are several demographic trends. The female labor force participation rate rose dramatically especially since 1960. For women in the prime child bearing ages (25-34) female labor force participation rose from 55.2% in 1963 to 81.3% in 1980.[1] Only teenagers and retirees (age 65-75) exhibit lower female participation rates in 1980 than in 1963. Male labor force participation rates decreased for teenagers and for men near retirement (age 55-64). Rates for other male age groups remained constant.

Family formation patterns have also changed as women in successively later cohorts delay entry into their first marriage. An interesting phenomenon is that young women are substituting consensual unions for marriage (Hoem and Rennermalm (1985)). Moreover, women of the younger cohorts form these unions at earlier ages than did their counterparts in earlier cohorts.[2]

Changes in fertility behavior are summarized in Table 2. Panel A reports the proportion of women of at least parity two by age and cohort. Panel B reports the same information for parity three. From Panel A the time to the second birth is stable for the first three cohorts (women born 1936-50). This evidence suggests that women in cohorts two and three have their first two children earlier than women in cohort one (compare proportions at age 25). There is a noticeable decline in the proportion having the first two births for the youngest cohort of women (born 1951-55).

From Panel B, the incidence of third births declines across cohorts. At age 30, a smaller proportion of women in each subsequent cohort have a third birth. The decline is most pronounced for the fourth cohort. The proportion of women with a third birth at age 25 is roughly half that of the previous cohorts. A broad characterization of recent Swedish fertility behavior is one of earlier

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[1] See Table 14c of Gladh and Gustafsson (1981). For the same period married female participation rates increased from 48.7% to 78.1%.

[2] Of the 1936-40 cohort, 34% experienced a union by age 20 versus 53% for the 1951-55 cohort. Only 5% of the 1951-55 cohort are married by age 20 versus 17% for the 1936-40 cohort.

but fewer births for women born between 1936 and 1950. For women in the most recent cohort (1951-55) there is evidence of delayed fertility and a hint that there will be fewer third births.

3.0 Empirical Results

This section reports the results of an extensive empirical analysis of Swedish fertility. Using our goodness of fit tests, we find that two models explain Swedish fertility equally well. The first is a purely demographic model of fertility. This representation of the birth process is parsimonious although it provides no explanation of the observed change in fertility across cohorts. The second model is consistent with neoclassical economic theory and uses aggregate measures of male and female wages to describe cohort specific fertility behavior. We find that female wages exert a negative or inhibiting effect on the timing and spacing of births and that the estimated effects are statistically and numerically important. Estimated female wage effects are robust to the inclusion or exclusion of variables measuring education, marital status, time trend, age, unemployment, proxies for public policies and lagged birth variables. Estimated male wage effects are positive. Higher male wages promote fertility. These estimated effects are less robust to the inclusion of marital status variables. They are robust to the inclusion of other control variables. For most specifications male income plays a numerically and statistically significant role in account for fertility.[1] We also find that temporally dependent unobservables are not empirically important in explaining Swedish fertility dynamics once account is made for stopping or mover-stayer behavior (the $P^{(j-1)}$ in expression (16)). This finding is in stark contrast to results we found for Hutterite women. (Heckman and Walker (1987a)). It justifies application of the piecemeal approach to Swedish fertility data.

Both of the best fitting models exhibit cohort drift in the estimated

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[1] In previous work (Heckman and Walker (1987b)) we report only the second model as the best fitting model because at the time of the writing of that paper we were not aware of (had not estimated) the first model.

parameters. Our analysis provides no direct evidence on the causes of inter-cohort fertility differences.

Our estimates of the model that incorporates economic variables provide indirect evidence on the source of the drift. It is consistent with the introduction of family and other pro-natal social programs in Sweden. Better micro-data on income and program benefits are required to substantiate this conjecture. The results reported in this paper suggest that such information will be empirically fruitful.

The presentation of our estimates is as follows. We first present estimates of the best fitting birth process model without economic variables. (Section 3.1). We next present estimates of the best fitting model that include economic variables. (Section 3.2). Section 3.3 compares the best fitting models. We estimate and evaluate an expanded model that nests the two best fitting alternative specifications of the birth process. Using the goodness of fit criterion, the expanded model performs (slightly) worse than either specialized version of it. In the last two subsections, we examine the best fitting economic model more closely. We document the drift in estimated parameters across cohorts. (Section 3.4). Finally, we simulate wage changes and measure their influence on third births. We find that a substantial portion of the effect of wages on age specific third birth rates operates through changing the age at which women come at risk for the third birth. (Section 3.5).

Table 3 lists the variables and scaling conventions used in our empirical analysis. For all estimated models, menarche is assumed to occur at age 13. Our analysis is qualitatively unchanged if we use other ages for menarche, e.g. age 15. The analysis is based on conception intervals--recorded live birth intervals minus nine months. Our estimates are virtually unchanged when we incorporated one and two month adjustments for post-partum ammenorrhea.

3.1. Demographic Models

Table 4 reports estimates of a model with Weibull duration dependence and with mover-stayer heterogeneity (i.e. $P^{(j-1)}$ present in the model but no serially correlated unobservables allowed for), background covariates and lagged birth intervals. The four columns of Table 4 correspond to the first four cohorts of the Swedish fertility survey, with the oldest cohort reported in the left-most column. For each cohort we report the estimated parameters of the hazard for the first three conception intervals. The estimated stayer proportions are reported below the estimates of the hazard parameters.

All transitions exhibit positive duration dependence. The estimated slope coefficients are statistically significant at conventional levels for all cohorts in transitions one and two and for the youngest cohort in the third transition. The background covariates-urban and white-collar-which are included to control for the initial conditions of the process exhibit little algebraic sign regularity or statistical signficance except for the white-collar coefficients in the first transition. For that transition white-collar background has an estimated negative and statistically significant effect across all cohorts: growing up in a white collar family lowers the probability of a first birth and increases the waiting time to the first birth.

Lagged birth durations are frequently use as proxies for serially correlated unobserved heterogeneity. (See Heckman and Walker (1987a).) This justification for incorporating lags suggests that the estimated cofficients on the previous spells should be negative. For example, if the unobservable is fecundability then women with low fecundability will have longer than average spells. A long first spell should be followed by long subsequent spells and hence a negative coefficient should be estimated in the hazard function. Only in the third transition are estimated coefficients of the previous spell lengths negative. In the second transition, the estimated coefficients for the first spell are positive. These estimated effects are statistically significant for the first and third cohorts. Since all women are assumed to start the fertility process at the same age, the length of the first spell measures the age at the start of the second spell. The estimated positive coefficient in the second transition on the lagged birth variable suggests catching up behavior. In the third transition coefficients on previous spell lengths are negative and statistically significant for all cohorts.

The estimated stayer proportions are stable across the first three cohorts for the first two parities (0 and 1). The estimated stayer proportion for the highest parity and third cohort is anomalously low. The stayer proportion of childless women in the fourth cohort is estimated to be about twice that of the previous cohorts. Delayed first births for this cohort may signal fewer completed births.

To evaluate the predictive power of this model we compute goodness of fit tests comparing observed with predicted parity distributions at various ages. Table 5 reports χ^2 tests for selected ages for each of the four cohorts. The first column for each cohort is the observed parity distribution in the sample. The second column for each cohort lists the predicted parity distribution. It is followed by the single cell χ^2 test statistic in column three. The joint χ^2 test statistic is listed beneath the single cell statistics for each age. At the bottom of the table are 5% critical values for one and three degrees of freedom. Because tests within a cohort are not independent, a Bonferroni test is used to evaluate the joint hypothesis that the predicted parity distributions fit at each of the selected ages. This test is based on the maximum χ^2 statistic over all age groups for each cohort. The size of the test depends on the number of age groups tested. Four age groups are used for cohorts one and two. Three are used for cohort three. Two are use for the fourth cohort. To achieve an overall α% significance level for a group with j age cell, requires a significance level of α/j for the maximum test statistic. Thus we require a 1.25% significance level for the maximum for cohort 4, 1.67% for cohort 3 and 2.5% for cohorts one and two. Critical values are reported at the base of the table.

For cohorts one, three and four, the joint test statistics at each age are well under the 5% critical value of 7.81. The joint test statistics indicate that the model does not explain the fertility of the second cohort at ages 25 and 30. The model passes these tests at these ages at the 1% level, however. The model fits the third transition rather well; the individual cell tests for parity three reject only at age 20 for cohort two (where there are few births to explain) and at age 30 for cohort one.

In results not reported here, we find that changing any one of the aspects of the fitted specification (deleting previous birth intervals, using other duration dependence specifications or dropping the mover-stayer model) produces a model at odds with the data.[2] Models with serially correlated unobservables are <u>not</u> the best fitting ones. The specification with estimates reported in Table 4 is the simplest model that fits the Swedish data. Wald tests of the hypothesis that the parameters are stable across cohorts for each transition are reported in Table 6. This hypothesis is soundly rejected for all three transitions. We have thus found a parsimonious model of intra-cohort fertility, but it provides no insight about changing behavior across cohorts.

3.2. A Neoclassical Economic Model

The models estimated in this section assess the impact of <u>current</u> wages of males and females on fertility transitions. We do not introduce measures of future wages or lagged wages into our analysis despite the importance of such

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[2] These results are reported in the conference version of the paper, (Heckman and Walker (1988)) and are available on request from the authors.

variables in many life cycle theories. Our reason for excluding wages from other periods in the estimation is a practical one. When future or lagged wages are included, they are highly correlated with current wages. Models augmented to include various summary measures of wages in other periods prove numerically unstable and difficult to estimate. In models in which agents have stationary expectations, are myopic, or in which wages are first order Markov, current wages are sufficient statistics for future wages. If preferences are separable, our estimated equations can be viewed as approximations to the decision rules for such models. Even if these assumptions are not satisfied, the estimates reported here enable us to estimate the net effect of wages (current and future) on fertility. Under the null hypothesis that the neoclassical model is false, current and future wages do not determine fertility. Evidence of wage effects contradicts that null.

Table 7 presents estimates of a Weibull model with mover-stayer heterogeneity controls ($P^{(j)}$ present but no serially correlated unobservables) using age-specific wages derived from published tax tables. Estimated coefficients of the female wage are negative and statistically significant for all transitions and for all cohorts. The estimated male income coefficients are all positive and are generally statistically significant. These estimates indicate that higher female wages lengthen birth intervals and reduce fertility. Higher male income increases the rate of arrival of births.

As in the best fitting purely demographic models, there is evidence of positive duration dependence. There is also evidence that women from white collar backgrounds tend to delay the first birth. For the first transition the estimated white collar coefficients are negative and statistically significant. No stable pattern emerges, however, for higher order transitions. In this model there is little effect of urban background on fertility. Estimated urban coefficients are as likely to be positive as negative and are usually not statistically significant.

To assess predictive power we compute goodness of fit tests for the Weibull model whose estimates are reported in Table 7. These tests are reported in Table 8. The format is the same as that of Table 5. The models pass the tests for all cohorts and at all ages except for cohort two at age 30. In that case, the Weibull underpredicts the number of childless women. For all other ages and cohorts, the test statistics indicate that a Weibull model with wages is consistent with the data. Moreover, 5% Bonferroni tests are passed by cohorts 1, 3, and 4. The model for the second cohort is barely rejected; the test statistic at age 30 is 11.0; the critical value of 10.9.

In results not reported here, we find that the estimated wage effects presented in Table 7 are robust to a variety of alternative model specifications.[3] Our estimated wage effects are robust to alternative assumptions about heterogeneity or duration dependence. The same pattern of wage coefficients is estimated with slightly less precision when manufacturing wages are used instead of the tax-table derived wages. The fact that aggregate wages are highly time trended raises the possibility that we have correlated two time trend variables (wages and fertility) and have merely produced "spurious regressions". However, we find that a linear time trend included as a covariate in the baseline model has a negligible effect on the estimated wage coefficients. Reparameterizing the model as a pure-age model (i.e. a specification in which waiting times between events are recorded in terms of age rather than duration) produces no sign reversals for the estimated coefficients which have approximately the same level of statistical significance as the baseline model reported in Table 7. A likelihood ratio test rejects the pure

[3] These are reported in the conference version of the paper, (Heckman and Walker (1988)) and are available on request from the authors.

age model in favor of the baseline duration model. Our results suggest that macro wage and income variables are not mere proxies for other time-trended or age-related variables which affect life cycle fertility.

We also examine the robustness of our results to the addition of control variables to the baseline set of covariates. Of particular interest is the addition of marital status variables. Recall that in the baseline model the male wage is entered only if the woman is married or within a consensual union. Our evidence of important male wage effects might be interpreted as evidence of marital status effects. Married women are more likely to have children than are single women. We find that when marital status variables are entered as separate regressors, estimated male income effects tend to weaken into statistical insignificance. However, models with marital status and male wages entered jointly do <u>not</u> pass our goodness of fit tests. In this sense our baseline model is the preferred specification.

We also examine the robustness of the estimates of the baseline model to the inclusion of a woman's education and to the inclusion of policy variables. Sweden has instituted a variety of family programs as well as additional programs designed to promote equality between men and women. Our measures of these programs are quite crude. We find little direct impact of these programs on fertility. Inclusion of measured policy and education variables does not overturn the baseline model.

The χ^2 goodness-of-fit tests select the baseline Weibull model with tax table wages. Such tests are informative in our application. The conventional criterion of selecting models on the basis of their signs and statistical significance of estimated coefficients is ineffective in the present analysis. Virtually all of the models we have estimated exhibit the same sign patterns and approximately the same significance level for the individual coefficients. As in the case of the purely demographic models, we find that models <u>without</u> serially correlated unobservables perform better on goodness of fit tests than do models with serially correlated unobservables.

3.3 Lagged Birth Intervals and Wages - Combining the Best Fitting Models

The class of best fitting models contains two members. The models differ only in terms of their regressors. It is natural to ask whether an extended model that nests both is superior in terms of goodness of fit. Somewhat surprisingly, the answer is no.

Estimates for the extended model are reported in Table 9. First transition estimates are identical, as they must be, to those reported in Table 8. For the second and third transitions the estimated coefficients for the economic covariates exhibit the same sign pattern as previously reported for the original economic model. Most estimated male income coefficients are reduced slightly in absolute value as are the female wage coefficients for the third transition. Introduction of lagged birth variables increases (in absolute value) the estimated female wage coefficients for the second transition. With wages added to the model estimated coefficients of the lagged birth variables for the second transition increase and become statistically significant. In the third transition, the inclusion of wages weakens the estimated effect of lagged births and there are some sign reversals. The estimated wage effects are robust to the inclusion of lagged birth intervals.

Table 10 reports χ^2 goodness of fit tests for the extended model with both wages and lagged birth variables in the regressor set. The extended model, like its demographic predecessor, fails the joint tests for the second cohort at ages 25 and 30. Unlike the best fitting models, the combined model fails at age 25 for the third cohort. The combined model fits the third parity cell at ages 25 and above. Strict application of our model selection criteria rejects the combined model as a member of the best fitting class. Test statistics reported in Table 10 suggest that the extended model overfits the intra-cohort fertility processes.

3.4 Parameter Instability Across Cohorts: Indirect Evidence on Policy Effects

Given the robustness of the sign and significance of the estimated economic coefficients across virtually all specifications, it is natural to ask if the estimated coefficients are stable across cohorts. The coefficients of the estimated birth process measure the total effect, directly through contraceptive choice and indirectly through labor force participation and household formation, of changes in wage income and other variables on fertility. If the policy environment in which individuals are operating is stable and tastes do not change the reduced form coefficients will be stable over time. Evidence of parameter drift can be interpreted as evidence of structural change due to policy or taste change. Wald tests for parameter stability are reported in Table 11. Using the tax table derived wages and income estimates, the estimated male income coefficients are significantly different across cohorts only for the first transition. Female wage coefficients are different across cohorts for all four cohorts.[4]

Inter-cohort patterns of estimated coefficients provide indirect evidence in support of policy effects. The pattern of declining coefficients for male income in the first transition across succesive cohorts is consistent with the interpretation that women in later cohorts are less dependent on the male's

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[4] Inferences about the stability of estimated female wage coefficients are sensitive to the assumed functional form of the duration dependence and wage series used. When manufacturing wages are used in a Weibull model, the female wage coefficients are not significantly different across cohorts. Similarly, in a model with quadratic duration dependence and tax-table derived wages, estimated female wage coefficients are not significantly different across cohorts. However, neither specification model passes our goodness of fit tests. See Heckman and Walker (1987a).

income in initiating the fertility process. Increasing child care benefits, greater female market participation and later age at first marriage all reduce the dependency of women on male income. These factors may also account for the observed rise in the fraction of women in consensual unions which have lower fertility rates.

The pattern of declining female wage coefficients across cohorts is also consistent with the hypothesis of reduced female attachment to the household. During the time period of our sample, female labor force particpation rates increased as did work conditioned child care benefits. Increasing the female wage rate increases the price of child services. The growth in work conditioned child care benefits makes the measured female wage an increasingly less accurate proxy for the price of time for later cohorts. Concomitant with the rising female wage has been the growth in free day care centers and public child care benefits which reduce the cost of child care and offset the increasing cost of the woman's time. These programs offset the negative effect of the rise in female wages on fertility.

It is useful to perform the counterfactual experiment of predicting the expected number of conceptions for a cohort using the preceding cohort's estimated coefficients and the cohort's own regressors. The best fitting economic model with coefficients estimates reported in Table 7 is simulated. The second column of Table 12 reports the expected number of conceptions by cohort for ages 25-35. The agreement between predicted and sample conceptions (column 1) is rather close. The predicted number of conceptions from the counterfactual simulation are reported in the third column of Table 12. Column four reports the change in predicted conceptions across cohorts (i.e. column 4 is the change in predicted fertility from that of the preceding cohort). The last two columns of Table 12 present one decomposition of the net changes listed in column 4. Column 5 reports the net change attributable to the change in coefficients across different cohorts. Assuming that cohort j has the same coefficients as cohort j-1 but allowing regressors to differ in the manner found in our sample, we overpredict the number of conceptions experienced by each cohort. The positive net effects reported in column four suggest that behavior across successive cohorts is becoming increasingly pronatal. This evidence is consistent with the notion that omitted policy variables have stimulated fertility.

The last column of Table 12 shows the net effect of wage change across cohorts. Using cohort j^s estimated coefficients with cohort $j\text{-}1^s$ covariate path, greatly reduces predicted fertility. The intercohort change in estimated parameters mitigates the negative effect of increased wages. This pattern of cohort drift suggests that the changing policy environment in Sweden has affected Swedish fertility.

3.5 Implications of the Estimates for the Effects of Wage Change on Life Cycle Fertility

Table 13 summarizes the effect of changes in tax table male and female wages on the pattern of life cycle fertility for cohort one women. The simulations increase the wage paths facing cohort one women and men by 12.2% at all ages. We evaluate the model at the mean of cohort one's variables. We use the coefficients reported in Table 7. The results reported for cohort one women are typical of those found for all cohorts of women when wages are changed in a similar fashion.

Panel A presents the impact of wage change on the distribution of fertility completed at age 40. This age is near the end of the childbearing years and is within the range of data on fertility histories available for cohort one women. There is little effect of wage change on the percent of women who are childless.[5] The principal effect of wage change is on the third birth. Higher wages for women substantially reduce third births. Higher wages for men substantially increase the proportion of women having a third birth. (Few Swedish women have more than three children so it is not possible to estimate transition functions to higher parities.) Panel B summarizes Panel A by presenting the impact of wage change on the predicted number of children at age 40. The female wage elasticity is more than twice the male wage elasticity. This highlights the central role of female wages on fertility.

Panel C reports the effect of wage change on interbirth intervals. The strongest impact of wages is on the time to the first birth. This is an effect conditioned on observed marriage or cohabitation patterns and likely understates (in absolute value) the net effect (allowing marital status to adjust). The effect of the female wage on the time to the first birth is especially strong. Higher female wages lead to longer interbirth intervals although the estimated effect on the transition time to the third birth is quite weak. These results indicate that the strongest effect of wages is on the postponement of the first birth. However the simulations reveal some effects of wages on transition times to higher order birth intervals. Wages affect both the level of births and the rate at which they are achieved.

It is of interest to examine the effect of wage change on third birth rates by age. Using a discrete approximation to the hazard and survivor functions, the third birth rate at age a is r(a):

[5] The best fitting Weibull model is not well suited to investigate the effect of wage change on childlessness. This is so because the Weibull model is nondefective-asymptotically the predicted proportion childless is $P^{(0)}$ and we do not parameterize $P^{(0)}$ to depend on wages.

$$r(a) = \bar{h}_3(a)\bar{S}_3(a) \times 1000$$

where $\bar{h}_3(a)$ is the probability of having a 3^{rd} birth at age a given that the woman has had two births and $\bar{S}_3(a)$ is the probability that the women is at risk for having a 3^{rd} birth.

Table 14 presents the impact of the wage changes considered in Table 13 on age-specific third birth rates. We decompose the effect of the wage change into a partial effect and a total effect. The partial effect is defined as

$$\Delta_p r(a) = \{\Delta\bar{h}_3(a)\}\bar{S}_3(a) \times 1000$$

i.e., the effect of wage change on the age specific rates <u>holding constant the population at risk to have a third birth</u>. The total effect is defined as

$$\Delta r(a) = \{\Delta\bar{h}_3(a)\}\bar{S}_3(a) + \bar{h}_3(a)\{\Delta\bar{S}_3(a)\}$$

and is inclusive of the effect of the wage change on changing the population at risk for pregnancy. The variations are taken with respect to changes in the wage paths.

The total effect measures the change in age specific birth rates that results when women of all ages are confronted with a new lifetime profile of wages and adjust their lifetime fertility accordingly. The partial effect measures the short run change in birth rates at age a when women have responded to baseline wages up to age a and modify only their age a specific fertility. It measures the effect of the new wage path conditional on the distribution of people at risk generated by the baseline wage path. The partial effect approximates short run responses to wage change of the sort observed over business cycles.[6]

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[6] The partial effect captures short run business cycle movements in fertility

The total effect of an increase in male wages is to increase third births and to concentrate age specific third birth rates into the age interval 30-40. The partial effect of male wage change is to increase third births at virtually all ages. Note that the relative magnitude of a female wage change on third birth rates is approximately twice that of a comparable male wage increase. Moreover, for almost every age long run impacts are larger (in absolute value) than the partial or short-run effects. This is a consequence of the net impact on the lower order parities; allowing the stock of women at risk for the third birth to adjust considerably augments the short run effect.[7] These accumulated stock effects account for 28% of the total impact of female wages on third births by age 40.

Figures 2 and 3 decompose the simulated change in age specific third birth rates into components attributable to wage change operating on each of the three parity specific hazard rates: the hazard rate for time to the first birth, the hazard rate for time to the second birth and the hazard rate for time to the third birth. Figure 2 - for the female wage change - graphs the base age specific third birth rate ("Base"). The curve labeled "1" displays the effect on the age specific third birth rate of changing the female wage profile <u>only in</u>

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exactly if agents use stationary (static) expectations to forecast future wages or if wages follow a random walk. Since we cannot estimate a model that distinguishes the impact of changes in current and future wages on fertility decisions, we cannot estimate the full business cycle response. If the female wage is transitorily higher today, it is likely that the decline in current fertility is higher than is measured in Table 14 since it is plausible that female time is substitutable over time. If the male wage is transitorily higher, it is likely that the partial effect of male wages reported in Table 14 overstates the effect of male income on age specific birth rates because the true wealth effect of a male wage change is small.

7 Recall that we condition on marital status. A higher male wage is likely to accelerate family formation and shift the unconditional birth rate schedule toward younger ages. A higher female wage is likely to postpone family formation and shift the unconditional birth rate schedule toward later ages.

the first birth hazard rate. The curve labeled "2" displays the effect on age specific third birth rates of changing the female wage in the first two hazard rates. The curve labeled "3" displays the total effect of the female wage change on age specific third birth rates. At the later ages, most of the effect of the female wage change is due to the direct effect of increased female wages operating through the hazard for the third birth, although there is still a non-neglible effect of wage change on the first two hazard rates. At the early ages, a substantial fraction of the total simulated change comes from the effect of female wage change operating through the hazard rate to the first birth and changing the proportion of women who are at risk to have a third birth.

Figure 3 records a parallel decomposition for the simulated male wage change. At the early ages, most of the effect of male wage change comes through the effect of male wages on the hazard rate for the first birth. Higher male wages place more women at risk to have a third birth. Around age 32 increased male income operating through the hazard rate for the time to the second birth actually decreases age specific third birth rates. At later ages, wages operating through the first two hazard rates and affecting the risk still account for a substantial portion of the increase in age specific third birth rates.

These simulations demonstrate the importance of accounting for the history of a birth process in evaluating the impact of changes in socioeconomic variables on third births. Changes that affect a woman's chances of being at risk for a third birth are an important component of the total effect of changes in socioeconomic variables on third births.

4.0 Conclusions

This paper considers the formulation, estimation and evaluation of multistate models of fertility dynamics. We discuss the role of unobservables in fertility models and the importance of accounting for unobservables in estimating fertility models that can be used in policy or intervention analysis. We discuss the dangers of piecemeal estimation strategies when serially correlated unobservables are part of the model specification. We go on to investigate the decline in third births for four cohorts of Swedish women. We estimate multistate birth process models using a robust semiparametric estimator that enables us to control for time-varying variables, serially correlated unobservables and general forms of duration dependence. We fit a variety of models to the data and use χ^2 goodness of fit tests to produce a class of best-fitting models. This class contains two members. The first is a model with lagged birth durations, Weibull duration dependence and mover-stayer heterogeneity. The second model uses aggregate age-specific male and female wage variables in place of the lagged birth variables to fit the cohort specific birth process. We find that the piecemeal approach can be applied without danger to the Swedish data.

For the model that includes wages we find that the estimated wage effects on fertility are statistically significant and economically plausible. Estimated female wage effects are robust to the inclusion or exclusion of variables measuring the woman's education, marital status, time trends and policy impacts. We find similar robustness for the estimated impact of male wages on fertility. The strength of the estimated male income effect is attenuated when marital status variables are entered as regressors. The best fitting models exclude marital status variables. Our results lend support to the claim of economists that wages - especially the wage of the female - play a central role in determining fertility dynamics.

The best-fitting model with wages exhibits drift in estimated wage coefficients across cohorts that is consistent with the introduction and enhancement of social programs designed to promote equality between men and women and programs that offer work conditioned child care benefits. The estimated positive effect of male income on fertility diminishes in size in more recent cohorts. This is consistent with growth in general benefits to women independent of marital status. The estimated negative effect of female wage rates on fertility also declines in more recent cohorts. This trend is consistent with the growth in work conditioned child care and maternity benefits that offset the impact of wages on fertility.

Simulating alternative male and female wage profiles, we separate the effect of wages on the entry into the risk set of women eligible for the third birth from the effect of wages on the age specific rate of third births conditional on women being at risk. We find that higher wages for women delay the onset of pregnancy and increase interbirth intervals. Higher female wages barely affect childlessness and have their primary effect on reducing third births. When wages are higher, pregnancy tends to be concentrated in a shorterspan of the life cycle that starts later in life.

Wages for men have quantitatively weaker effects on fertility than do the wages of women. Higher male wages reduce a woman's time to first birth, reduce interbirth intervals and barely affect the proportion of childless women in the population. The impact of higher male wages is to increase the proportion of families with three children and to expand the span of years that women engage in childbearing.

The direct effect of wages on third births holding constant the stock of women at risk for the third birth accounts for 72% of the total impact of a permanent wage change on completed births at age 40. The indirect effect of wages of placing women at risk for a third birth (the stock effect) accounts for the remaining 28%. An empirical analysis that restricts attention only to third birth transition rates considerably underestimates the impact of wages on third births.

The robustness of the estimated wage effects on fertility and their interpretative plausability provide encouraging evidence that improved longitudinal measures of household income and programs benefits will be of great value in predicting Swedish fertility and accounting for cohort drift.

The unimportance of serially correlated unobservables in analyzing the Swedish data indicates that computationally less demanding piecemeal estimation schemes that ignore the history of the process being studied will yield consistent estimates. Unlike the case for societies like the Hutterites where serially correlated fecundity differences play a central role in accounting for fertility, in modern Sweden serially correlated unobservables play a negligible role.

This finding is consistent with the greater variability across people in wealth, status, and economic resources in modern societies than is the case for primitive economic societies where inequality in wealth and resources is much less pronounced. Our suggests that in modern societies, variation in socio-economic variables may swamp the variation in fecundity in accounting for fertility dynamics.

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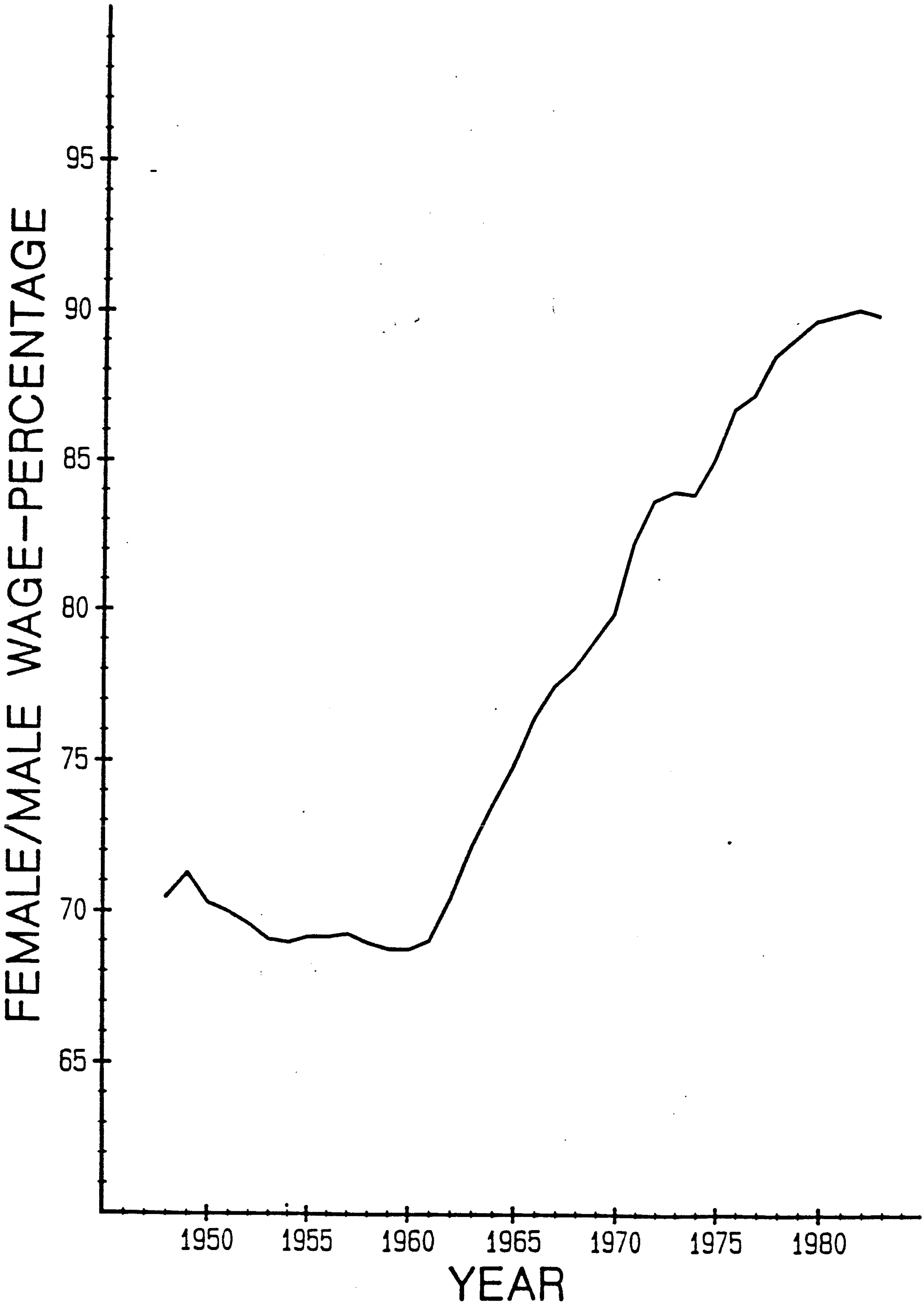

FEMALE/MALE WAGE-PERCENTAGE
95
90
85
80
75
70
65
1950
1955
1960
1965
1970
1975
1980
YEAR

Figure 1

Female Wage Change
3rd Birth Rate per 1000
0.0
5.0
10.0
15.0
20.0
25.0
22.0
26.0
30.C
34.0
38.0
42.0
Age
Base
1
2
3

Figure 2


Male Wage Change
3rd Birth Rate per 1000
0.0
5.0
10.0
15.0
20.0
25.0
22.0
26.0
30.0
34.0
38.0
42.0
Age
Base
1
2
3

Figure 3

Table 1

Cases Analyzed and Parity distribution at Survey Date
By Cohort

Number of Cases

	Cohort 1 (Born 1936-1940)	Cohort 2 (Born 1941-1945)	Cohort 3 (Born 1946-1950)	Cohort 4 (Born 1951-1955)
	486	997	1006	1034

Parity Distribution at Survey Date

Parity	Cohort 1	Cohort 2	Cohort 3	Cohort 4
0	60	114	161	385
1	74	179	200	280
2	207	449	474	304
3	104	207	148	60
4	29	43	17	3
5	8	3	6	2
6	3	2		
7	1			

Table 2

Proportion Achieving Parities 2 and 3 by Age and Cohort

Panel A

Proportion Achieving Parity 2

	Cohort 1 (Born 1936-40)	Cohort 2 (Born 1941-45)	Cohort 3 (Born 1946-50)	Cohort 4 (Born 1951-55)
age 25	0.260	0.282	0.275	0.213
age 30	0.568	0.564	0.562	

Panel B

Proportion Achieving Parity 3

	Cohort 1 (Born 1936-40)	Cohort 2 (Born 1941-45)	Cohort 3 (Born 1946-50)	Cohort 4 (Born 1951-55)
age 25	0.057	0.049	0.047	0.025
age 30	0.181	0.151	0.131	

Table 3

Definition of Variables utilized in Analysis

duration	Number of months/100 spent in the current spell.
male income	Age-specific average annual income in 1970 Kronor for males based on Swedish Personal Income Tax Returns data. This variable is zero if the woman is single. Expressed as thousands of Kronor
female wage	Age-specific average hourly wage rates in 1970 Kronor for females based on Swedish Personal Income Tax Returns data. Expressed in tens of Kronor.
urban	A dummy variable = 1 if the woman grew up in an urban area and (Stockholm, Gothenburg, Malmo) of Sweden and zero otherwise.
white collar	A dummy variable = 1 if the woman's father was in a white collar occupation when she was growing up and zero otherwise.
bdur1	The length of the first conception interval, measured in months/100.
bdur2	The length of the second conception interval, measured in months/100.

Table 4

Birth Process Model with Weibull Duration Dependence
Background Covariates, Lagged Duration Dependence and
Mover Stayer Heterogeneity

$(K = 1, \lambda_{1j} = 0, j = 1,2,3)$

	Cohort Born 1936-40		Cohort Born 1941-45		Cohort Born 1946-50		Cohort Born 1951-55	
	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err
Variable/Transition	First Conception		First Conception		First Conception		First Conception	
intercept	.2219	.0745	.1704	.0529	.4261	.0552	.4927	.0920
ℓn duration	1.6270	.0983	1.5900	.0794	1.5762	.0833	1.8948	.1353
urban	-.0734	.0918	.0807	.0634	-.0108	.0772	-.0205	.1018
white collar	-.2397	.0970	-.2145	.0679	-.4601	.0893	-.5447	.1067
	Second Conception		Second Conception		Second Conception		Second Conception	
intercept	1.2561	.1247	1.7142	.1074	1.6860	.1209	1.9322	.1783
ℓn duration	.3732	.0582	.5584	.0523	.6111	.0532	.8075	.0897
urban	.1921	.0992	.2152	.0685	-.1307	.0776	.2624	.1213
white collar	.0147	.0994	-.0570	.0733	.0591	.0801	-.0828	.1322
bdur1	.2124	.1051	.0182	.0979	.2992	.1069	.2740	.2055
	Third Conception		Third Conception		Third Conception		Third Conception	
intercept	1.4839	.2681	2.0301	.2890	1.6148	.3933	3.4050	.7111
ℓn duration	.2735	.1074	.1989	.0955	.1805	.1203	.9456	.2556
urban	.5911	.1914	.0240	.1610	-.4028	.1904	-.7267	.3486
white collar	-.1529	.1934	.2818	.1807	.2006	.2035	.2895	.3832
bdur1	-.1353	.2453	-1.0541	.2121	-1.2686	.2570	-.8221	.6720
bdur2	-.2427	.0571	-.1759	.0340	-.0670	.0417	-.1408	.0982
μ Estimates:*								
	Parity 0		Parity 0		Parity 0		Parity 0	
μ	-1.9603	.1379	-2.0619	.1009	-1.8069	.1033	-.9483	.1109
Implied Probability	.1234		.1129		.1410		.2792	
	Parity 1		Parity 1		Parity 1		Parity 1	
μ	-1.5825	.1330	-1.5694	.0967	-1.5741	.1061	-1.2244	.1383
Implied Probability	.1704		.1723		.1716		.2272	
	Parity 1		Parity 2		Parity 2		Parity 2	
μ	.0968	.1467	-.1110	.1364	-.5028	.3091	.3406	.2493
Implied Probability	.5242		.4723		.3769		.5843	
Log-Likelihood	-860.0		-1677.8		-1454.1		-1118.4	

* Stayer Probabilities $P^{(j)} = (1 + e^{-\mu_j})^{-1}$.

Table 5

χ^2 Goodness of Fit Tests For A Model With Weibull Duration Dependence, Lagged Birth Durations, and Mover-Stayer Heterogeneity

$(K = 1, \lambda_{1j} = 0, j = 1,2,3)$

	Cohort 1 (Born 1936-1940)			Cohort2 (Born 1941-1945)			Cohort3 (Born 1946-1950)			Cohort4 (Born 1951-1955)		
Number of Conceptions	act[a]	pred[b]	test	act	pred	test	act	pred	test	act	pred	test
by age 20												
n = 0	0.776	0.795	1.15	0.771	0.784	0.99	0.744	0.764	2.08	0.814	0.826	1.00
n = 1	0.161	0.146	0.86	0.170	0.154	1.84	0.178	0.175	0.06	0.141	0.133	0.54
n = 2	0.051	0.046	0.31	0.052	0.048	0.42	0.067	0.051	5.36	0.041	0.036	0.68
n = 3+	0.012	0.013	0.01	0.007	0.014	3.46	0.011	0.010	0.02	0.004	0.005	0.12
joint			1.28			5.59			5.65			1.43
by age 25												
n = 0	0.399	0.416	0.59	0.367	0.401	4.83	0.375	0.384	0.34	0.484	0.484	0.00
n = 1	0.268	0.289	1.14	0.288	0.294	0.17	0.267	0.293	3.21	0.252	0.267	1.06
n = 2	0.247	0.216	2.82	0.259	0.224	6.80	0.285	0.252	5.81	0.222	0.204	2.28
n = 3+	0.086	0.079	0.40	0.086	0.081	0.41	0.073	0.071	0.04	0.042	0.046	0.38
joint			3.73			8.68			6.85			2.44
by age 30												
n = 0	0.183	0.181	0.01	0.173	0.169	0.08	0.183	0.186	0.08			
n = 1	0.216	0.244	2.02	0.215	0.254	8.18	0.210	0.221	0.74			
n = 2	0.383	0.395	0.33	0.425	0.399	2.90	0.451	0.430	1.83			
n = 3+	0.218	0.179	4.94	0.187	0.178	0.64	0.156	0.162	0.30			
joint			5.79			8.43			1.94			
by age 35												
n = 0	0.134	0.129	0.10	0.123	0.118	0.24						
n = 1	0.165	0.170	0.09	0.174	0.180	0.27						
n = 2	0.416	0.441	1.29	0.450	0.446	0.08						
n = 3+	0.285	0.260	1.69	0.253	0.256	0.05						
joint			2.14			0.51						

[a] sample probability.

[b] predicted probability.

χ^2 critical values:

df	10%	5%	1%
3	625	7.81	11.35
1	1.64	2.74	5.41

Bonferroni Statistics

2.5%	1.67%	1.25%
9.35	10.25	10.88

Table 6

Wald Tests of Parameter Stability Across Cohorts 1-4
For Estimates Reported Table 7

All Coefficients of Parity Specific Hazard Restricted To Be Equal Across Cohorts

Transition	Degree of Freedom	Test Statistic	Probability
1	12	28.44	.0048
2	15	51.41	.0000
3	18	102.89	.0000

Tests on Lagged Birth Variable Coefficients Restricted To Be Equal Across Cohorts

Transition	Degree of Freedom	Test Statistic	Probability
2	3	4.35	.2264
3	6	18.82	.0045

TABLE 7

WEIBULL DURATION BIRTH PROCESS MODEL WITH WAGE AND INCOME VARIABLES DERIVED FROM TAX TABLES AND MOVER-STAYER UNOBSERVED HETEROGENEITY CONTROL

($K = 1,\ \lambda_{1j} = 0,\ j = 1,2,3$)

	cohort 1		cohort 2		cohort 3		cohort 4	
	(Born 1936-1940)		(Born 1941-1945)		(Born 1946-1950)		(Born 1951-1955)	
	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err
Variable/Transition	first conception		first conception		first conception		first conception	
intercept	1.0440	.1941	1.3680	.1440	1.5668	.1625	1.4911	.2201
ℓn duration	1.9203	.2521	2.3907	.1980	2.0380	.1905	2.3097	.2496
male income II	1.0850	.0723	.8242	.0467	.9926	.0590	.8809	.0589
female wage II	-4.7380	.5740	-3.9623	.3070	-3.3834	.2729	-2.6895	.2576
urban	-.0361	.0947	.0865	.0657	-.0482	.070	.0178	.0922
white collar	-.2575	.1015	-.1878	.0685	-.4230	.0797	-.4225	.0939
Variable/Transition	second conception		second conception		second conception		second conception	
intercept	2.1088	.1852	2.3618	.1506	2.2872	.1628	2.4284	.2447
ℓn duration	.4586	.0701	.6205	.0537	.6177	.0526	.7735	.0810
male income II	.5765	.0961	.6558	.0778	.7708	.093	.8480	.1229
female wage II	-3.0311	.4429	-2.6007	.2650	-1.9492	.2474	-1.8167	.2976
urban	.1760	.1123	.2348	.0716	-.1830	.0779	.2022	.1231
white collar	.1119	.1170	-.0929	.0761	.0546	.0801	-.1546	.1316
Variable/Transition	third conception		third conception		third conception		third conception	
intercept	2.4871	.4181	2.5754	.3897	2.0369	.5804	4.5067	.9231
ℓn duration	.4808	.1377	.4566	.1177	.3796	.1360	1.1799	.2415
male income II	.5059	.2705	.2355	.1111	.0623	.1182	.8124	.3116
female wage II	-4.8733	.9947	-3.0653	.3752	-1.9892	.3702	-2.9032	.8660
urban	.4753	.2108	.0732	.1612	-.4024	.1607	-.9104	.3647
white collar	.0301	.2218	.1570	.1698	1357	.1696	.2099	.3523
Estimates:[1]								
	Parity 0		Parity 0		Parity 0		Parity 0	
μ_0	-2.3801	.1820	-2.6004	.1499	-2.6132	.1811	-2.0172	.2760
Implied Probabilities	.0847		.0691		.0683		.1174	
	Parity 1		Parity 1		Parity 1		Parity 1	
μ_1	-1.8403	.1620	-1.817	.1174	-1.9005	.1297	-1.6755	.1854
Implied Probabilities	.1370		.1322		.1301		.1577	
	Parity 2		Parity 2		Parity 2		Parity 2	
μ_2	-.4540	.2163	-.6603	.2612	-2.9326	3.9330	.1205	.3107
Implied Probabilities	.3884		.3407		.0506		.5301	
Log-Likelihood =	-707.8		-14178		-1189.7		-956.6	

[1] Stayer probabilities $P^{(j)} = (1 + e^{-\mu_j})^{-1}$

TABLE 8

CHI-SQUARE TESTS OF WEIBULL DURATION DEPENDENCE MODELS WITH WAGE AND INCOME VARIABLES DERIVED FROM TAX TABLES AND MOVER-STAYER UNOBSERVED HETEROGENEITY CONTROL

$(K = 1, \lambda_{1j} = 0, \; j = 1,2,3)$

Number of Conceptions	Cohort 1 (Born 1936-1940) act[a]	pred[b]	test	Cohort 2 (Born 1941-1945) act	pred	test	Cohort 3 (Born 1946-1950) act	pred	test	Cohort 4 (Born 1951-1955) act	pred	test
by age 20												
n= 0	0.776	0.760	0.67	0.771	0.743	4.23	0.744	0.721	2.74	0.814	0.800	1.41
n= 1	0.161	0.163	0.03	0.170	0.189	2.51	0.178	0.208	5.49	0.141	0.160	2.77
n= 2	0.051	0.062	0.87	0.052	0.054	0.07	0.067	0.058	1.46	0.041	0.037	0.43
n= 3	0.012	0.015	0.25	0.007	0.014	3.45	0.011	0.013	0.38	0.004	0.003	0.05
joint			1.25			6.60			6.82			3.06
by age 25												
n= 0	0.399	0.395	0.05	0.367	0.380	0.74	0.375	0.376	0.01	0.484	0.483	0.00
n= 1	0.268	0.299	2.40	0.288	0.310	2.26	0.267	0.293	3.25	0.252	0.276	2.87
n= 2	0.247	0.230	0.80	0.259	0.234	3.56	0.285	0.258	4.10	0.222	0.203	2.66
n= 3	0.086	0.076	0.71	0.086	0.076	1.38	0.073	0.073	0.00	0.042	0.038	0.42
joint			2.94			6.07			5.25			4.54
by age 30												
n= 0	0.183	0.149	5.05	0.173	0.147	5.44	0.183	0.181	0.03			
n= 1	0.216	0.246	2.35	0.215	0.254	8.36	0.210	0.225	1.39			
n= 2	0.383	0.407	1.25	0.425	0.418	0.24	0.451	0.437	0.85			
n= 3	0.218	0.198	1.24	0.187	0.181	0.34	0.156	0.157	0.00			
joint			7.68			11.00			1.56			
by age 35												
n= 0	0.134	0.113	2.24	0.123	0.109	2.23						
n= 1	0.165	0.176	0.42	0.174	0.189	1.67						
n= 2	0.416	0.435	0.79	0.450	0.461	0.40						
n= 3	0.285	0.276	0.26	0.253	0.241	0.74						
joint			2.94			4.01						

[a] sample probability.

[b] predicted probability.

χ^2 critical values:

df	10%	5%	1%
3	625	7.81	11.35
1	1.64	2.74	5.41

Bonferroni Statistics

2.5%	1.67%	1.25%
9.35	10.25	10.88

Table 9

Birth Process Model with Weibull Duration Dependence Background Covariates, Lagged Duration Dependence, Age Specfic Wages and Mover Stayer Heterogeneity Control

($K = 1, \lambda_{1j} = 0, j = 1,2,3$)

	Cohort Born 1936-40		Cohort Born 1941-45		Cohort Born 1946-50		Cohort Born 1951-55	
	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err	Estimate	Std-Err
Variable/Transition	First Conception		First Conception		First Conception		First Conception	
intercept	1.0441	.1950	1.3685	.1444	1.5664	.1627	1.4915	.2212
ℓn duration	1.9204	.2512	2.3917	.1985	2.0372	.1903	2.3103	.2513
male income	1.0851	.0725	.8248	.0468	.9926	.0593	.8809	.0590
female wage	-4.7382	.5754	-3.9630	.3078	-3.3827	.2731	-2.6899	.2584
urban	-.0361	.0954	.0857	.0657	-.0482	.0712	.0178	.0923
white collar	-.2576	.1019	-.1873	.0684	-.4230	.0798	-.4225	.0940
bdur1	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
bdur2	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
	Second Conception		Second Conception		Second Conception		Second Conception	
intercept	2.2025	.2017	2.5379	.1629	2.5067	.1843	2.5957	.2633
ℓn duration	.6506	.0953	.8409	.0823	.8645	.0852	.9824	.1174
male income	.4244	.1109	.5426	.0825	.6927	.0936	.8062	.1236
female wage	-4.3147	.6229	-3.6444	.3580	-2.8944	.3410	-2.6655	.3992
urban	.1662	.1163	.2079	.0761	-.1837	.0825	.1534	.1263
white collar	.0565	.1239	-.1122	.0806	.0597	.0864	-.1712	.1328
bdur1	.8722	.2587	.9163	.2247	1.0366	.2461	1.1680	.3897
bdur2	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
	Third Conception		Third Conception		Third Conception		Third Conception	
intercept	3.0067	.4706	2.5793	.4163	2.0603	.5974	4.8728	.9617
ℓn duration	.4367	.1880	.3609	.1390	.3432	.1607	1.0349	.3009
male income	.3709	.3407	.1717	.1195	.0680	.1251	.9042	.3409
female wage	-4.4546	1.0784	-2.7280	.4970	-1.8425	.5481	-2.1571	1.2074
urban	.4956	.2063	.0140	.1516	-.4001	.1601	-.9155	.3589
white collar	.0634	.2183	.1305	.1610	.1286	.1703	.1569	.3486
bdur1	.2663	.5424	.1544	.3610	-.0882	.5053	-.7708	1.0825
bdur2	-3.1479	.8375	-1.5724	.5081	-.4852	.6498	-3.3132	1.5610
μ Estimates:*								
	Parity 0		Parity 0		Parity 0		Parity 0	
μ	-2.3801	.1821	-2.5996	.1498	-2.6133	.1812	-2.0172	.2762
Implied Probability	.0847		.0692		.0683		.1174	
	Parity 1		Parity 1		Parity 1		Parity 1	
μ	-1.8692	.1708	-1.9009	.1217	-1.9112	.1336	-1.7814	.2144
Implied Probability	.1336		.1300		.1288		.1441	
	Parity 2		Parity 2		Parity 2		Parity 2	
μ	-.8348	.2747	-1.0608	.4123	-3.1455	5.3881	.0749	.2952
Implied Probability	.3026		.2572		.0413		.5187	
Log-Likelihood	-691.4		-1402.1		-1179.8		-949.8	

* Stayer Probability $P(j) = (1 + e^{-\mu_j})^{-1}$.

Table 10

χ^2 Goodness of Fit Tests For A Model With Weibull Duration Dependence, Lagged Births, Background Covariates, Age-Specific Wages, and Mover-Stayer Heterogeneity

	Cohort 1 (Born 1936-1940)			Cohort 2 (Born 1941-1945)			Cohort 3 (Born 1946-1950)			Cohort 4 (Born 1951-1955)		
Number of Conceptions	act[a]	pred[b]	test	act	pred	test	act	pred	test	act	pred	test
by age 20												
n = 0	0.776	0.755	1.12	0.771	0.743	4.23	0.744	0.725	1.95	0.814	0.803	0.85
n = 1	0.161	0.168	0.21	0.170	0.189	2.50	0.178	0.206	5.02	0.141	0.157	2.06
n = 2	0.051	0.057	0.26	0.052	0.054	0.07	0.067	0.056	2.05	0.041	0.036	0.52
n = 3+	0.012	0.020	1.40	0.007	0.014	3.45	0.011	0.012	0.16	0.004	0.003	0.16
joint			2.07			6.60			6.57			2.55
by age 25												
n = 0	0.399	0.393	0.08	0.367	0.380	0.75	0.375	0.379	0.09	0.484	0.488	0.10
n = 1	0.268	0.306	3.55	0.288	0.318	4.13	0.267	0.305	6.84	0.252	0.283	4.82
n = 2	0.247	0.212	3.53	0.259	0.224	7.33	0.285	0.245	9.31	0.222	0.191	7.08
n = 3+	0.086	0.088	0.01	0.086	0.079	0.78	0.073	0.071	0.04	0.042	0.038	0.36
joint			5.21			9.70			11.70			9.51
by age 30												
n = 0	0.183	0.145	6.14	0.173	0.149	4.79	0.183	0.182	0.00			
n = 1	0.216	0.247	2.61	0.215	0.259	10.42	0.210	0.239	4.67			
n = 2	0.383	0.398	0.50	0.425	0.409	1.14	0.451	0.427	2.64			
n = 3+	0.218	0.209	0.26	0.187	0.183	0.13	0.156	0.153	0.09			
joint			7.65			12.24			5.17			
by age 35												
n = 0	0.134	0.110	2.94	0.123	0.110	1.88						
n = 1	0.165	0.176	0.45	0.174	0.200	4.55						
n = 2	0.416	0.431	0.47	0.450	0.445	0.12						
n = 3+	0.285	0.283	0.02	0.253	0.245	0.38						
joint			3.25			5.54						

[a] sample probability: [b] predicted probability.

χ^2 critical values:

df	10%	5%	1%
3	625	7.81	11.35
1	1.64%	2.74	5.41

Bonferroni Statistics

2.5%	1.67%	1.25%
9.35	10.25	10.88

TABLE 11

WALD TESTS OF EQUALITY ECONOMIC COEFFICIENTS ACROSS COHORTS FOR EACH TRANSITION AGE-SPECIFIC INCOMES DERIVED FROM TAX TABLES*

Weibull Model $(K = 1, \lambda_{1j} = 0, \ j = 1,2,3)$

Male income II:

Transition	Test Statistic	Degrees of Freedom	Probability
first	11.37	3	0.010
second	3.99	3	0.263
third	6.53	3	0.088

Female Wage II:

Transition	Test Statistic	Degrees of Freedom	Probability
first	16.38	3	0.001
second	8.45	3	0.038
third	9.46	3	0.024

*The Wald Tests reported in this paper are based on the unrestricted estimates and are given for each transition density.

Table 12

Counterfactual Simulations Of Expected Number of Conceptions at the Indicated Age Using Cohort-Specific Birth Process Estimates of Best Fitting Economic Model

Cohort	(1) Sample Values	(2) Predicted Using Own Covariates and Estimated Parameters	(3) Predicted Using Own Covariates and Estimates From Preceding Cohort	(4) Observed Net Change Between Successive Cohorts	(5) Net Change Due to Changes in Coefficients	(6) Net Change Due to Changes in Covariates
<u>Age 25</u>						
1	1.040	1.061	——	——	——	——
2	1.064	1.068	.686	.007	.382	-.375
3	1.056	1.073	.662	.005	.411	-.406
4	0.820	0.826	.624	-.247	.202	-.449
<u>Age 30</u>						
1	1.636	1.741	——	——	——	——
2	1.626	1.708	1.175	-.033	.533	-.566
3	1.580	1.617	1.042	-.091	.575	-.666
<u>Age 35</u>						
1	1.852	1.931	——	——	——	——
2	1.833	1.879	1.366	-.052	.513	-.565

Table 13

The Impact of Wage Change on Life Cycle Fertility

	Base	Change Due To A 12.2% Rise in Male Wage	Change Due To A 12.2% Rise in Female Wage
	Panel A		
% Childless	8.6	- .55	.03
% Having Exactly One Child by age 40	15.8	-2.40	.89
% Having Exactly Two Children by age 40	57.3	-3.40	.70
% Having Exactly Three Children by age 40	18.3	5.70	-9.9
	Panel B		
Predicted Number of children by age 40	1.85	.09	-.19
Implied Elasticity	—	.35	-.89
	Panel C		
Mean Time in Months* To			
First conception (Measured from age 13)	171	-8	19
Second conception (Measured from first birth)	51	-5	7
Third conception (Measured from second birth)	73	-1	1

*Evaluated at age 40 for those who experienced the event.

Table 14

Impact of Wage Changes on Third Birth Rates By Age

Age	Base 3rd Birth Rate Per 1000	Change Due To 12% Rise in Male Wage		Change Due to 12% Rise in Female Wage	
		Partial Effect	Total Effect	Partial Effect	Total Effect
20	.0	.0	.0	.0	.0
21	.1	.0	.0	.0	.0
22	.1	.0	.0	.0	.0
23	.3	.0	.0	-.2	-.3
24	.4	.0	.0	-.1	-.2
25	.5	.1	.2	.0	-.2
26	.7	-.1	.0	-.3	-.5
27	1.6	.3	.7	-.8	-1.2
28	2.2	.5	1.1	-.6	-1.4
29	4.1	.0	1.1	-1.4	-2.8
30	5.1	.7	2.2	-1.6	-3.3
31	7.1	1.0	2.9	-1.3	-3.8
32	9.1	2.9	5.4	-3.1	-6.0
33	14.0	3.9	7.1	-5.4	-8.9
34	16.4	4.2	7.0	-6.5	-10.1
35	19.0	4.0	6.3	7.7	-11.3
36	20.7	6.3	8.0	-8.4	-11.6
37	23.0	3.5	4.0	-9.1	-11.8
38	23.5	4.7	4.5	-9.3	-11.1
39	23.9	5.6	4.7	-9.6	-10.4
40	22.9	6.5	5.0	-9.3	-9.0
Total		42.6	59.0	-74.7	-103.9