Published in final edited form as:

Popul Stud (Camb). 2013 March ; 67(1): 7–23. doi:10.1080/00324728.2012.737473.

Multidimensional Life Table Analysis of the Effect of Child Mortality on the Total Fertility Rate in India

Hassan Eini-Zinab

Program on Population and Health Studies at the East-West Center in Honolulu, Hawaii, USA

Abstract

This paper develops a new method for estimating the effect of child mortality on the total fertility rate (TFR). The method is based on discrete-time survival models of parity progression that enable construction of a multivariate multidimensional life table of fertility, the four dimensions of which are woman's age, parity, duration in parity, and number of previous child deaths. Additional socioeconomic variables are included in the set of predictor variables in the underlying survival models of parity progression. The life table, which is multivariate, yields a replacement rate, which measures the effect of one additional child death on the TFR. The method is illustrated by applying it to three Indian National Family Health Surveys. Major findings are that dead children are incompletely replaced, and that the replacement rate rises as the total fertility rate falls, reflecting women's increasing ability to control their fertility.

Keywords

fertility; TFR; child mortality; multidimensional life table; survival models; replacement rate; India

There are two major mechanisms by which child mortality affects fertility. The first is the *replacement effect*, which has both biological and volitional components. The biological component arises from premature termination of breastfeeding due to the death of a child, resulting in a shorter period of lactational infecundity and, consequently, a shorter following birth interval in the absence of contraception. The volitional component arises from a conscious decision to replace a child who has died, by temporarily stopping contraception until another birth occurs. The second major mechanism is the *insurance* or *hoarding effect*, which arises when couples in high mortality settings anticipate mortality risk by having one or more extra children beyond their desired family size in order to be sure to attain their target number of surviving children (Preston 1978; Knodel 1978). The insurance effect has never been successfully estimated. The present paper develops a new method for estimating the overall replacement effect of child mortality on fertility (biological and volitional replacement combined) from individual-level survey data, with an illustrative application to data from three successive National Family Health Surveys (NFHS) in India.

Existing methods for estimating the replacement effect of child mortality on fertility from individual-level survey data fall in two main groups. The first group includes methods that estimate the effect of child mortality on parity progression ratios (PPRs) and birth intervals (e.g., Vallin and Lery 1978; Ben-Porath 1978; Hashimoto and Hongladarom 1981). The second group includes methods that regress children ever born (CEB) on number of child

deaths and other predictors (e.g., Olsen 1980; Trussell and Olsen 1983; Zhang 1990; Kabir et al. 2001). Studies of the effect of child mortality on fertility in India have used one or the other of these two methods (e.g., Pandey et al. 1998; Syamala 2001; Bhalotra and Soest 2008).

The new method developed in this paper takes a different approach, by incorporating parity progression, birth intervals, and regression (in this case, discrete-time hazard regression), all in the same method, with the total fertility rate (TFR) as the fertility measure of principal interest. The method focuses on the effect of child mortality on the TFR because the TFR is the most widely used summary measure of fertility as a consequence of its simple intuitive meaning as the mean number of births that a woman will eventually have if she survives to the end of the reproductive age span.

Input data for the new method are individual-level birth histories and demographic and socioeconomic characteristics of potential mothers. Discrete-time survival models of parity progression, with one such model for each parity transition, are fitted to these data, and the fitted models are then used to generate single-year birth probabilities by woman's age, parity, duration in parity, number of previous child deaths, and socioeconomic characteristics. These birth probabilities are used to construct a multivariate multidimensional life table of fertility. In this life table, women are followed by age, parity, duration in parity, and number of previous child deaths, one year at a time until they reach age 50. The TFR is then calculated as the average number of life table births per woman by age 50, and overall child mortality is calculated as the average number of life table child deaths (regardless of child's age) per woman by age 50. The effect of child mortality on fertility is calculated as the replacement rate, R , defined as the effect of a one-unit increase in the number of life table child deaths per woman on the TFR.

R or any other measure calculated from the multidimensional life table can be either a cohort measure or a period measure, depending on whether the input data are cohort data or period data. In the illustrative application to Indian data, cohort data consist of person-year observations at earlier ages of women age 45–49 at time of survey, derived from the birth histories) and period data include person-year observations in the 5-year period before survey of women aged 10–49 at time of survey (again derived from the birth histories). A person-year observation has attached to it information about the woman's socioeconomic and demographic characteristics, including her history of births and child deaths. The cohort estimates and the period estimates are both useful and to some extent complementary. The cohort estimates have the disadvantage of referring to fertility and child mortality that occurred mostly in the fairly distant past, but the advantage of pertaining to a real group of women. By contrast, the period estimates have the disadvantage of pertaining to a synthetic cohort of women, but the advantage of being contemporary. Methodology for calculating R is the same in either case, because the methodology does not distinguish whether a person-year observation pertains to a real cohort or to a synthetic cohort. The life table, whether a cohort life table or a period life table, is multivariate in the sense that any measure calculated from it can be tabulated by categories or selected values of one socioeconomic variable while controlling for other socioeconomic variables. Measures that can be calculated include, but are not limited to, age-specific fertility rates, parity progression ratios, mean and median birth intervals and ages at childbearing, total fertility rate, and the replacement rate R .

The methodology in more detail

Background

The expansion of the dimensions of the multidimensional life table hark back to Sir David Cox's 1972 influential paper that by marrying regression models to life tables revolutionized much demographic analysis. The new method builds on earlier work, starting with a fertility estimation method developed by Feeney (Feeney 1986; Feeney and Yu 1987). Feeney's method, which is not multivariate, is based on life tables of parity progression, with one life table for each parity transition. Each such life table yields a period parity progression ratio (PPR). A period TFR is calculated from the period PPRs. The life tables for the various parity transitions also yield estimates of mean and median closed birth intervals by birth order.

Using discrete-time survival models of parity progression, Retherford et al. (2010a, 2010b) extended Feeney's method by making it multivariate. The survival model for any given parity transition i to $i+1$ yields a set of model-predicted values of the probabilities P_{it} , where i denotes parity, t denotes duration in parity, and P_{it} denotes the probability of a next birth between durations t and $t+1$ for a woman of starting parity i . The probabilities P_{it} , which are multivariate in the sense defined earlier, enable construction of a multivariate life table of parity progression for the particular parity transition under consideration, yielding a multivariate PPR for that transition. A multivariate TFR is then calculated from the multivariate PPRs for all the transitions. This method is referred to here as the P_{it} method.

Retherford et al. (2011) subsequently extended the methodology further by adding woman's age A (upper case and lower case letters are used for variable names and coefficients, respectively) at starting parity to the set of predictor variables in each of the underlying discrete-time survival models of parity progression. Collectively, these models ultimately yield multivariate estimates of the birth probabilities P_{ait} , where a denotes woman's age at duration t . The multivariate probabilities P_{ait} are then used to construct a multivariate multidimensional life table, the three dimensions of which are age, parity, and duration in parity. This life table spans all parity transitions, in contrast to the separate life tables for the various parity transitions in the P_{it} method. This multidimensional life table yields multivariate estimates of TFR and a number of related measures. The related measures include PPRs, age-specific fertility rates (ASFRs), mean and median closed birth intervals, and mean and median ages at childbirth by child's birth order and for all birth orders combined. Retherford et al. (2011) refer to this extension of the P_{it} method as the P_{ait} method.

The new method for estimating the effect of child mortality on fertility builds on the P_{ait} method by adding two variables representing number of previous child deaths to the set of predictor variables in the underlying survival models of parity progression. The birth probabilities generated by these survival models are denoted P_{aitmn} , where m and n denote number of previous child deaths at ages $a-1$ and a , respectively. The probabilities P_{aitmn} are then used to generate a multivariate 4-dimensional life table from which the replacement rate R is calculated. Henceforth, the new method for estimating the effect of child mortality on the TFR is referred to here as the P_{aitmn} method. In the present application to Indian data, the multidimensional life table begins at age 10 and ends at age 50.

The P_{aitmn} method in more detail

In the P_{aitmn} method, child mortality is, in essence, a one-year lagged predictor variable. As already noted, m denotes number of previous child deaths at age $a-1$, and n denotes number of previous child deaths at age a . The difference between m and n is either 0 or 1, indicating whether a child death occurred between ages $a-1$ and a . (If a woman experienced two or

more child deaths in a one-year age interval, all but one of those child deaths are randomly allocated to the next or (if necessary) subsequent age intervals for that woman in the underlying data set, so that the woman experiences no more than one child death in an age interval.) In this context a refers to woman's age. Child's age plays no role in the analysis. Child deaths can occur at any age of child, no matter how old the child is.

The one-year lag minimizes the problem of reverse-causation from fertility to child mortality, because a birth to a woman of parity i between ages a and $a+1$ cannot have much of an effect on whether any of her previous children died prior to age a . If, however, the pregnancy corresponding to the birth occurred between ages $a-1$ and a , it may have had some effect on her care of her previous children and therefore on their risk of mortality between ages $a-1$ and a . The P_{aitmn} method ignores this risk, which is assumed to be very small.

The P_{aitmn} method yields not only all the fertility measures yielded by the P_{ait} method, but also the following measures: child mortality rates by woman's age, mean and median ages of woman at child death, mean number of child deaths per woman by age 50, and the replacement rate R . All of these additional measures are derived from the multidimensional life table and are therefore multivariate in the sense defined earlier.

The person-year data set for a particular parity transition makes it easy to include time-varying predictor variables in the survival model for that parity transition. For example, in the case of a dummy variable U representing urban/rural residence for a woman who moves from rural to urban, person-year observations up to the time of migration are coded rural ($U = 0$), and person-year observations after that time are coded urban ($U = 1$). It is also easy to include time-varying effects of predictor variables. In the case of U , one simply interacts U with duration in parity (t) or some function of duration in parity (e.g., t and t^2) (Retherford et al. 2010a, 2010b; Retherford et al. 2011). (In the illustrative application to India that comes later, data limitations do not allow the socioeconomic variables to be specified as time-varying. Their effects, however, are treated as time-varying.)

Figure 1 depicts graphically the transitions of women along the multidimensional life table's multiple dimensions for each of the first three parity transitions 1–2, 2–3, and 3–4, assuming that the starting parity in any given parity transition was attained at woman's age a , so that $t = 0$ at age a . The 0–1 transition is omitted, because there are, as yet, no previous births that could have died. For notational clarity, Figure 1 replaces m with M_m . M_m is, however, just another way of writing m .

Panel 1 of Figure 1 portrays the 1–2 parity transition. Consider a woman who starts in state M_0 at age a duration 0 (i.e., $t = 0$). At age $a+1$ duration 1, there is still only one child mortality state M_0 , because number of previous child deaths m at age a is still zero. A woman in state M_0 at age $a+1$ duration 1 continues in that state until age $a+2$ duration 2 if she did not experience a child death between age a duration 0 and age $a+1$ duration 1. Alternatively, if the woman experienced a child death between age a duration 0 and age $a+1$ duration 1, she moves from M_0 to M_1 between age $a+1$ duration 1 and age $a+2$ duration 2. Once a woman attains child mortality state M_1 , she remains in that state until one year after she has a second birth (in which case she is no longer in parity transition 1–2) or reaches ten years of duration in parity without having yet had a second birth (which is the situation depicted in the figure). The sequence is truncated at duration 10 because it is assumed that if the woman has not had a next birth by duration 10, she will never have a next birth. The logic of Panels 2 and 3 is similar, the difference being that the number of possible child mortality transitions increases as parity increases.

So far, the functional form of the discrete-time survival models has not been specified. A number of models are available, the most commonly used one being the discrete-time logit model. As in the earlier papers on the P_{it} and P_{ait} methods (Retherford et al. 2010a, 2010b; Retherford et al. 2011), the P_{aitmn} method, as developed here, uses the complementary log-log (CLL) model instead, for reasons given in the earlier papers. The multidimensional life table estimates of TFR, R , and other measures are virtually identical, however, regardless of which of the two models is used.

Two of the four basic predictor variables in the underlying CLL model for the 1–2 transition are woman's age A at starting parity and woman's duration in parity, where duration in parity is specified sometimes by t and sometimes by nine dummy variables $T_1, T_2, \dots, T_9$ indicating particular one-year age intervals, with the tenth interval chosen as the reference category. The other two basic predictor variables are D_1 and D_2 . D_1 and D_2 are yet another way of writing m and n ; i.e., $D_1 = m$ and $D_2 = n$.

The CLL model for parity transitions higher than 0–1, with residence and education as examples of socioeconomic predictors, can be written as

$$P = 1 - \exp\{-\exp[a + b_1T_1 + b_2T_2 + \dots + b_9T_9 + A(c_1 + c_2t + c_3t^2) + A^2(d_1 + d_2t + d_3t^2) + D_1(e_1 + e_2t + e_3t^2) + D_2(f_1 + f_2t + f_3t^2) + U(g_1 + g_2t + g_3t^2) + E_L]\}$$

where P is the predicted probability of a next birth in a one-year interval; $T_1, T_2, \dots, T_9$ are dummy variables representing the first nine life table time intervals (with the tenth interval as the reference category); t is a counter variable (equal to 1, 2, ..., 10) that also denotes duration interval; A is age at starting parity; D_1 and D_2 represent previous child mortality as defined earlier; U is urban/rural residence (1 if urban, 0 if rural); and E_L and E_H are dummy variables representing low and high education, with illiterate as the reference category. The dummies $T_1, T_2, \dots, T_9$ represent basic life table time, but the counter variable t is used in the interaction terms. A ranges from 10 to 49 and t ranges from 1 to 10. (t starts at 1 instead of 0 for reasons having to do with how the model is fitted to the data.) A model-predicted value of P_{aitmn} for $t = 3$ and specified values of the other predictor variables, for example, is obtained by setting $t = 3$, $T_3 = 1$, and $T_1 = T_2 = T_4 = T_5 = \dots = T_9 = 0$.

The model equation for the 0–1 transition is similar, except that t ranges from 1 to 30 (corresponding to ages 10–40), the set of T_i variables is expanded to $T_1, T_2, \dots, T_{29}$, and the age variable A and the child mortality variables D_1 and D_2 are dropped. A is dropped because it is constant at age 10, and D_1 and D_2 are dropped because there are no previous births or child deaths. In the underlying person-year data set for the 0–1 transition, first births below age 10 (if any) are re-coded to age 10 (the age at which the multidimensional life table begins), and first births after age 40, which are negligible in number, are ignored. In the expanded data set for the 1–2 transition, however, first births after age 40 (up to a maximum of 49) are included in the set of starting events. Likewise, in the expanded data sets for the 2–3 and higher-order transitions, all second or higher-order births, regardless of woman's age or duration in parity, are included in the set of starting events, and all next births at durations 0–9, regardless of woman's age, are included in the set of terminal events.

The specifications of the predictor variables in the equations are much the same as in the earlier paper on the P_{ait} method (Retherford et al. 2011). An A^2 term is included as well as an A term in the set of predictor variables, because the rise and fall of fecundity as age increases suggest that the effect of starting age on parity progression will be non-linear, and that a quadratic specification of starting age will adequately capture this non-linearity. The effects of both A and A^2 are specified as time-varying (i.e., t -varying) because the effect of duration in parity on parity progression changes as starting age increases, due not only to biological influences (changing fecundity) but also to behavioral influences. An example of

a behavioral influence is that couples are more likely to settle into a life style with few or no children the longer they delay marriage and childbearing (Retherford et al. 2011).

Except for the variable D_2 , the set of predictor variables in equation (1) includes all two-way interactions among the predictor variables in order to achieve a more flexible fit to the data. (A flexible fit is needed to ensure that, in the cohort case, the model-predicted TFR is very close to the conventionally calculated TFR. See Retherford et al. (2011) for further discussion of this point). In the case of D_1 and D_2 , one needs to allow that the effects of both D_1 and D_2 can be non-linear over age and duration within a particular parity transition. Therefore, D_1 and D_2 are both interacted with t , t^2 , A , and A^2 . It is necessary to interact a socioeconomic predictor only with D_1 , however. The reason is that D_1 and D_2 together measure a woman's child mortality trajectory over a one-year age or duration interval, and the aim is to interact this trajectory with each of the socioeconomic predictors. Only one of the variables D_1 and D_2 is needed to do this. D_1 is chosen over D_2 because, for any particular woman, the value of D_1 at the start of the interval is the same regardless of whether she experiences a child death during the interval.

As one proceeds to very high parity transitions, the MLE estimation procedure for fitting the model may not converge to a solution, due to small numbers of cases. When non-convergence occurs, the dummy variables $T_1, \dots, T_9$ are replaced by t and t^2 in equation (1). Eventually, as one proceeds to very high parity transitions, even models with a quadratic specification of duration in parity in terms of t and t^2 cannot be estimated because of non-convergence problems stemming from the dummy variable specifications of the socioeconomic predictor variables. One then needs to use an open-ended parity transition (e.g., 10+ to 11+), for which the expanded data sets for the single-parity transitions comprising the open-ended parity transition (e.g., 10–11, 11–12, 12–13, etc.) are pooled. One first tries the following CLL model for this open-ended parity transition:

$$P = 1 - \exp\{-\exp[a + b_1 T_1 + b_2 T_2 + \dots + b_9 T_9 + A(c_1 + c_2 t + c_3 t^2) + A^2(d_1 + d_2 t + d_3 t^2) + D_1(e_1 + e_2 t + e_3 t^2) + D_2(f_1 + f_2 t + f_3 t^2) + U(g_1 + g_2 t + g_3 t^2) + E_L I]\}$$

where I denotes a woman's parity at the start of the year within a person-year observation (before any birth that may have occurred within that person-year observation). If, because of convergence problems, this equation cannot be estimated, one then replaces the dummy variables $T_1, \dots, T_9$ with t and t^2 in equation (2) and tries to fit that model. If that does not work, one has to broaden the open parity interval to include one more lower parity transition (the 9–10 in this example, so that the open parity interval becomes 9+ to 10+).

Collectively, the CLL models for the various parity transitions ultimately yield model-predicted birth probabilities P_{aitmn} for specified values of the socioeconomic variables. The probabilities P_{aitmn} for a particular set of values of the socioeconomic characteristics are then used to calculate a multidimensional life table from which TFR, R , and other measures are calculated. Basic formulae for calculating this life table are presented in the Appendix.

Equations (1) and (2) can also be used to calculate unadjusted and adjusted probabilities P_{aitmn} by socioeconomic characteristics. "Unadjusted" means "without controls", and "adjusted" means "with controls". Unadjusted probabilities P_{aitmn} by categories or selected values of a particular socioeconomic variable are obtained from model equations that omit all other socioeconomic variables from the model equations. Adjusted probabilities by values or categories of a particular socioeconomic variable are obtained from model equations that retain not only the particular socioeconomic variable, which is treated as the main socioeconomic variable, but also all the other socioeconomic variables, which are controlled by holding them constant at their duration-specific (i.e., t -specific) mean values in the particular parity transition under consideration when varying the main socioeconomic

variable from one category (or selected value, in the case of a continuous variable) to the next. (A companion working paper (Eini-Zinab 2011) provides further details on how this is done.)

The unadjusted probabilities P_{aitmn} are then used to construct an unadjusted multidimensional table for each category of the socioeconomic variable of interest, and the adjusted probabilities P_{aitmn} are used to construct an adjusted multidimensional life table for each category of that socioeconomic variable. Unadjusted and adjusted values of TFR, R , and other measures are then calculated from these unadjusted and adjusted life tables. Any of these measures can always be presented in the form of a simple bivariate table or graph (showing a value of the measure for each category of the socioeconomic predictor variable), regardless of the complexity of the underlying CLL models.

Calculation of child mortality rates from the multidimensional life table

The first step is to define a child mortality rate D_a (not to be confused with the variables D_1 and D_2 in the underlying CLL models) as

$$D_a = (\sum S_{aitmn}) / 1,000 \quad (3)$$

where 1,000 is the radix of the multidimensional life table; S_{aitmn} is the number of life table women who “survive” to age a , parity i , duration in parity t , and number of previous child deaths m and n ; and the summation is over i , t , m , and n , but only for those combinations of m and n where $n = m + 1$ (i.e., those combinations of m and n indicating that a child death occurred in the previous one-year age interval). D_a is then the one-year-lagged age-specific child mortality rate for women age a in the life table.

If the summation in equation (3) is also over a , the result is total number of child deaths per woman at the end of the life table, denoted as D .

Both D_a and D are affected by the number of life table births as well as by conventionally measured child mortality rates by age of child. In the case of D , for example, the higher the number of births in the life table, the higher the value of D .

Calculation of the replacement rate R from the multidimensional life table

One can also construct a multidimensional life table by setting child mortality equal to zero in the multidimensional life table formulae. As explained in the Appendix, this is done by setting partitioning factors Q_{aitm} equal to zero in the multidimensional life table equations, where Q_{aitm} is the probability that a woman age a , parity i , duration t , and number of previous child deaths m experienced a child death during the previous year. This procedure allows child mortality to be eliminated from the multidimensional life table (by setting Q_{aitm} equal to zero) while preserving the effects (i.e., coefficients) of the other predictor variables on fertility with child mortality controlled in the underlying CLL equations (by setting D_1 and D_2 equal to zero). This life table is referred to here as the child-mortality-free multidimensional life table, denoted as MDLT_{NCM}, where NCM denotes “no child mortality”. The child-mortality-free MDLT is calculated from probabilities $P_{a,i,t,0,0}$ estimated from CLL models that include the variables D_1 and D_2 , which are both set to zero in the fitted CLL model equations.

All measures derived from the MDLT_{NCM} are also child-mortality-free. These measures can be compared with corresponding measures calculated from the multidimensional life table derived from the probabilities P_{aitmn} , discussed earlier, that do not set, m , n , D_1 , D_2 , and Q_{aitm} equal to zero. This MDLT is referred to here as MDLT_{WCM}, where WCM denotes

“with child mortality”. Any differences between the two sets of measures are attributable to the effect of child mortality on fertility.

Several replacement measures can be constructed. One of them is

$$\Delta TFR = TFR_{WCM} - TFR_{NCM} \quad (4)$$

Another measure is the proportional increase in TFR due to child mortality, calculated as $[(TFR_{WCM} - TFR_{NCM}) / TFR_{NCM}]$. Our preferred measure, however, is the replacement rate R , calculated as

$$R = \frac{\Delta TFR}{D} \quad (5)$$

R indicates the effect of a one-unit increase in number of child deaths per woman (all women, not just mothers) on the TFR. As such, R is a measure of the extent to which a dead child is replaced by another birth.

Validation of the P_{aitmn} method

The approach to validating the P_{aitmn} method is the same as that used to validate the earlier P_{ait} method on which the P_{aitmn} method builds. In the case of the P_{ait} method, the validation procedure compared, where possible, fertility measures derived by the P_{ait} method with corresponding estimates derived by the birth history method and the P_{it} method. This was done using cohort data from the 2003 Philippines Demographic and Health Survey. The P_{ait} method was considered valid if, for real cohorts, the estimates derived by the various methods turned out to be close to the same. The test showed that they were close to the same (Retherford et al. 2011). In the case of the P_{aitmn} method, they have also been found in a companion working paper to be close to the same, based on tests on cohort data from India's 1992–93 National Family Health Survey (Eini-Zinab 2011).

One does not expect as good agreement when the various methods are applied to period data. The reason is that, in the case of the P_{ait} method, the distribution of women by parity and duration in parity at any given age can differ substantially between the actual population and the multidimensional period life table population (Retherford et al. 2011). In the case of the P_{aitmn} method, the distribution of women by parity, duration in parity, and number of previous child deaths can likewise differ substantially between the actual population and the multidimensional period life table population.

Application of the P_{aitmn} method to India's National Family Health Surveys

Between 1990 and 2009, India's TFR fell by 33 per cent from 4.0 to 2.7, and its under-five child mortality rate declined 44 per cent from 118 to 66 (see UNICEF website, Country Statistics section, India). These moderately high and declining levels of fertility and child mortality, together with publicly available data from three National Family Health Surveys (NFHS), make India a suitable candidate for applying the P_{aitmn} method. The application to India is illustrative and not meant to be a full substantive study.

The socioeconomic predictors included in the application of the P_{aitmn} method to India's NFHS surveys are residence (urban/rural), education (illiterate, low, high), wealth (low, medium, high), religion (Hindu, other religion), scheduled caste/scheduled tribe (SC/ST, other), and region (North, East, South, and West). Low education includes some primary or completed primary, and high education includes all levels of education above primary. Wealth is based on an index constructed by Macro International (Rutstein and Johnson, 2004). Break points in the wealth index for low, medium, and high are chosen with the goal

(imperfectly achieved) of having one-third of the women in each of the three categories. The break points vary from one survey to the next. When religion is used as a control variable, “other” includes all non-Hindu women. When religion is used as the main socioeconomic predictor variable, “other” includes Muslims only. Scheduled castes and scheduled tribes are castes and tribes that the Government of India identifies as socially and economically backward and in need of special protection from social injustice and exploitation. North includes the states of Haryana, Himachal Pradesh, Jammu, Madhya Pradesh, Punjab, Rajasthan, Uttar Pradesh, New Delhi, Uttaranchal (only in NFHS-3), and Chhattisgarh (only in NFHS-3). East includes the states of Assam, Bihar, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, West Bengal, Arunachal Pradesh, Tripura, Sikkim (only in NFHS-2 and NFHS-3), and Jharkhand (only in NFHS-3). South includes the states of Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu. West includes the states of Goa, Gujarat, and Maharashtra. Except for Sikkim, the states included only in NFHS-2 or NFHS-3 are new states that have been split off from existing states. Sikkim could not be included in NFHS-1 because of political disturbances.

Table 1 shows how sample women are distributed on the socioeconomic characteristics in each of the three surveys. Women age 45–49 contribute to the cohort analysis, and women age 10–49 contribute to the period analysis, in which the period is the five-year window immediately preceding the survey under consideration. The table shows increasing proportions with urban residence, high education, and Scheduled Caste/Scheduled Tribe membership over the three surveys. The proportions by religion and region are fairly stable over the three surveys. Trends in the proportions in the wealth categories are not meaningful because the wealth categories are defined somewhat differently in each survey, with the goal of keeping the proportion in each wealth category close to one-third.

Table 2 presents estimates of selected multidimensional life table measures, based alternatively on cohort and period data from the three surveys. In the case of the cohort estimates, TFR_{WCM} and TFR_{NCM} both declined by about 0.9 child. The cohort estimates of D show that the number of child deaths per woman also declined considerably. The cohort estimate of ΔTFR (calculated as the difference between TFR_{WCM} and TFR_{NCM}) remained roughly constant at about 0.3 child over the three surveys. The cohort estimate of the replacement rate R (calculated as $\Delta TFR/D$) rose substantially, from 0.33 in NFHS-1 to 0.55 in NFHS-3, reflecting increased control over fertility through increased use of contraception and abortion, as well as more time to replace dead children as age at completion of childbearing declined. The cohort estimates of mean A_d (mean age of woman at child death among those women who experienced a child death) indicate a decline of somewhat more than a year over three surveys. This occurred because the reduction of births (and, therefore, of early childhood deaths) was concentrated at higher parities and older ages of women (for evidence of these reductions, see the published NFHS reports (International Institute for Population Sciences (IIPS) 1995; International Institute for Population Sciences (IIPS) and ORC Macro 2000; International Institute for Population Sciences (IIPS) and Macro International 2007).

The period results in Table 2 are less dramatic, apparently because the period of major decline in fertility and major increase in contraceptive use preceded the five-year period before NFHS-1. (For the trends in contraceptive use, see the published NFHS reports). As the table shows, the period estimates of TFR_{WCM} declined by about half a child over the three surveys. TFR_{WCM} fell further than TFR_{NCM} , so that ΔTFR fell substantially. Percent changes in ΔTFR and D were similar, so that the period estimate of R hardly changed over the three surveys. R is higher in the period case. This is expected, because desired family size and fertility have been falling and contraception has been increasing over time, implying substantially more fertility control among women age 10–49 during the 5-year

period before survey than among the cohort of women age 45–49 at time of survey, who had most of their children during earlier periods when fertility control was not so widely practiced.

Tables 3 and 4 show unadjusted and adjusted estimates of total fertility rates (TFR_{WCM}) and replacement rates R by socioeconomic characteristics for cohorts and periods, based on the three NFHS surveys. For both cohorts and periods, TFR fell, in most cases substantially, in every socioeconomic category between NFHS-1 and NFHS-3. In any given survey, TFR tends to be higher for women who are rural, illiterate, low-wealth, Muslim, and Scheduled Caste/Scheduled Tribe. By region, TFR is highest in the North and lowest in the South. Urban/rural differentials in TFR mostly disappear when other socioeconomic variables are controlled. Wealth differentials and Scheduled Caste/Scheduled Tribe differentials in TFR are also greatly reduced when other variables are controlled. By contrast, education differentials, religion differentials, and regional differentials in the TFR tend not to be reduced very much when other socioeconomic variables are controlled, indicating that the effect of each of these three variables is largely independent (though not completely so) of the effects of other variables in the two tables. Adjustment for other socioeconomic variables tends to reduce differences in TFR across categories of the main socioeconomic variable under consideration.

Tables 3 and 4 also show that, when the TFR is low, R tends to be high, as expected. In the case of cohorts, R does not differ much between urban and rural. R tends to be higher for those with more education in NFHS-1 but unexpectedly higher for those with less education in NFHS-3. R is consistently higher for those with high wealth than those with medium or low wealth. R is also consistently much higher for Hindus than for Muslims. Differences in R between SC/ST and non-SC/ST tend to be small. Differences in R between regions also tend to be small. In almost all cases, R increases over the three surveys. In the case of education, however, R increases a great deal for illiterates and those with low education but hardly changes at all for those with high education. Those with high wealth have the highest replacement rate. For each category of each socioeconomic variable, the period estimate of R for each survey in Table 4 tends to be higher than the cohort estimate, for reasons previously mentioned in the discussion of Table 2. Adjustment for the other socioeconomic variables almost always has the effect of reducing differences in R across categories of the main socioeconomic variable.

Standard errors of the model-predicted estimates of TFR and its components, including the replacement rate R and related measures, can be calculated by the jackknife method, following the approach used in DHS surveys for calculating standard errors of aggregate measures such as TFR. Retherford et al. (2010a, 2010b) used the jackknife to estimate standard errors of TFR and its components in their earlier papers that developed the P_{it} method. Application of the jackknife was found to be very computer-intensive, requiring weeks of two fast desktop computers operating around the clock. Application of the jackknife promises to be a great deal more computer-intensive in the case of the P_{aitmn} method, which is much more complicated than the P_{it} method, and which is applied here to much larger samples.

For these reasons, the jackknife is not applied in this paper. The SAS programs that estimate the underlying CLL models routinely print out coefficients and their standard errors, however. There are 26,064 estimated coefficients in the various models that underlie the results for India that are reported in this paper. Because of the very large number of coefficients and the complexity of the new method, the coefficients and their standard errors are not very useful; indeed, this is a major reason for focusing instead on model-predicted values of TFR and the replacement rate R .

Conclusion

Although the P_{aitmn} method is complex, involving the construction of multivariate multidimensional life tables of fertility, final results are in the form of simple bivariate tables that are easily understood not only by demographers and statisticians but also by policy makers and program managers. The method, which is applicable to period data as well as cohort data, is multivariate in the sense that any measure derived from the multidimensional life table can be tabulated or graphed by values or categories of one socioeconomic variable while holding constant the other socioeconomic variables included in the underlying discrete-time survival models.

The principal measure of interest is the replacement rate R , which is defined as the incremental increase in the TFR due to a one-child increase in the total number of child deaths per woman, as measured at the end of the multidimensional life table. In the illustrative application of the method to India's NFHS surveys, results show that replacement of dead children is incomplete but tends to increase over time. Overall, R increases from 0.33 to 0.55 in the cohort case but only from 0.51 to 0.53 in the period case between NFHS-1 and NFHS-3. R tends to be higher in the period analysis than the cohort analysis in NFHS-1 and NFHS-2, but not in NFHS-3, by which time cohort R and period R converge. A more general conclusion is that, both longitudinally and cross-sectionally, when fertility is relatively low, replacement tends to be relatively high, reflecting relatively high contraceptive use rates that enable couples to replace dead children more effectively and efficiently. Cross-sectionally, adjustment for other socioeconomic variables almost always reduces differences in R across categories of the main socioeconomic variable under consideration.

Acknowledgments

Support for this research was provided by Grant 1R01HD057038 from the U.S. National Institutes of Health. I am grateful to Robert Retherford for helpful comments on earlier drafts of this paper. Computer programs (in SAS) are available from the author on request (eini@hawaii.edu or h_eini_z@yahoo.com).

REFERENCES

- Ben-Porath, Y. Fertility response to child mortality: Microdata from Israel. In: Preston, SH., editor. The effects of infant and child mortality on fertility. NY: Academic Press; 1978. p. 161-180.
- Bhalotra, Sonia; van Soest, Arthur. Birth-spacing, fertility and neonatal mortality in India: Dynamics, frailty, and fecundity. *Journal of Econometrics*. 2008; 143(2):274-290.
- Cox, David R. Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*. 1972; 34(2):187-220.
- Eini-Zinab, Hassan. Multivariate life table methodology for estimating the effect of child mortality on the total fertility rate and its components. East-West Center Working Paper 123. Honolulu: East-West Center; 2011. <http://www.eastwestcenter.org/fileadmin/stored/pdfs/popwp123.pdf>.
- Feeney, Griffith. Period parity progression measures of fertility in Japan. NUPRI Research Papers Series no. 35. Tokyo: Nihon University Population Research Institute; 1986.
- Feeney, Griffith; Yu, Jingyuan. Period parity progression measures of fertility in China. *Population Studies*. 1987; 41:77-102. [PubMed: 11612059]
- Hashimoto, Masanori; Hongladarom, Chira. Effects of child mortality on fertility in Thailand. *Economic Development and Cultural Change*. 1981; 29(4):781-794.
- International Institute for Population Sciences (IIPS) and Macro International. National Family Health Survey(NFHS-3) 2005-06: India: Volume I. Mumbai: IIPS; 2007.
- International Institute for Population Sciences (IIPS) and ORC Macro. National Family Health Survey (NFHS-2), 1998-99. India. Mumbai: IIPS; 2000.

- International Institute for Population Sciences (IIPS). National Family Health Survey (MCH and Family Planning), India 1992–93. Bombay: IIPS; 1995.
- Kabir, Ahmad. The effect of child mortality on fertility. *The Sciences*. 2001; 1(6):377–380.
- Knodel, J. European populations in the past: family-level relations. In: Preston, SH., editor. *The effects of infant and child mortality on fertility*. NY: Academic Press; 1978. p. 21–45.
- Olsen, Randall J. Estimating the effect of child mortality on the number of births. *Demography*. 1980; 17(4):429–443. [PubMed: 7461232]
- Pandey, Arvind; Choe, Minja Kim; Luther, Norman Y.; Sahu, Damodar; Chand, Jagdish. *Infant and Child Mortality in India. National Family Health Survey Subject Reports Number 11*. Mumbai: International Institute for Population Sciences and Honolulu: East-West Center; 1998.
- Preston, Samuel H. *The Effects of Infant and Child Mortality on Fertility*. NY: Academic Press; 1978.
- Retherford, Robert D.; Eini-Zinab, Hassan; Choe, Minja Kim; Ogawa, Noa Hiro; Matsukura, Rikiya. Further development of methodology for multivariate analysis of the total fertility rate and its components based on birth-history data. East-West Center Working Paper 122. Honolulu: East-West Center; 2011. (revised May 2011). <http://www.eastwestcenter.org/fileadmin/stored/pdfs/popwp122.pdf>
- Retherford, Robert D.; Eini-Zinab, Hassan; Choe, Minja Kim; Ogawa, Noa Hiro; Matsukura, Rikiya. Forthcoming. Multidimensional life table estimation of the total fertility rate and its components. *Demography*. Published online on December 2012.
- Retherford, Robert D.; Ogawa, Naohiro; Matsukura, Rikiya; Eini-Zinab, Hassan. Multivariate analysis of parity progression-based measures of the total fertility rate and its components using individual-level data. East-West Center Working Paper No. 119 (revised January 2010). Honolulu: East-West Center; 2010a. <http://www.eastwestcenter.org/fileadmin/stored/pdfs/POPwp119.pdf>.
- Retherford, Robert D.; Ogawa, Naohiro; Matsukura, Rikiya; Eini-Zinab, Hassan. Multivariate analysis of parity progression-based measures of the total fertility rate and its components. *Demography*. 2010b; 47(1):97–124. [PubMed: 20355686]
- Rutstein, Shea O.; Johnson, Kiersten. *The DHS Wealth Index*. DHS Comparative Reports 6. Calverton, MD: ORC Macro; 2004.
- Syamala TS. Relationship between infant and child mortality and fertility: An enquiry into Goan Women. *Indian Journal of Pediatrics*. 2001; 68(12):1111–1115. [PubMed: 11838563]
- Trussell, James; Olsen, Randall. Evaluation of the Olsen technique for estimating the fertility response to child mortality. *Demography*. 1983; 20(3):391–405. [PubMed: 6628779]
- Vallin, J.; Lery, A. Estimating the increase in fertility consecutive to the death of a young child. In: Preston, SH., editor. *The effects of infant and child mortality on fertility*. NY: Academic Press; 1978.
- Zhang, Junsen. Mortality and fertility: How large is the direct child replacement effect in China? *Journal of Population Economics*. 1990; 3(4):303–314. [PubMed: 12283655]

Appendix

Constructing the multidimensional life table from the birth probabilities

P_{aitmn}

The life table begins at woman's age 10 and ends at woman's age 50. The radix of the life table is 1,000 women at age 10. The life table allows that a woman's children may die, but not the woman herself (consistent with the conventional calculation of the TFR from ASFRs, which also assumes zero mortality of women).

Life table variables are the following:

m :	For a woman at exact age a , m is her number of previous child deaths as of one year ago when she was exact age $a-1$
n :	For a woman at exact age a , n is her number of previous child deaths at exact age a
P_{aitmn} :	Probability that a woman age a , parity i , duration t , and previous child deaths m and n has a birth between exact ages a and $a+1$
S_{aitmn} :	Number of life table women who “survive” to age a , parity i , duration in parity t , and previous child deaths m and n
S_{aitm*} :	Defined as $S_{a,i,t,m,m} + S_{a,i,t,m,m+1}$
Q_{aitm} :	Partitioning factor (partitions S_{aitm*} into $S_{a,i,t,m,m}$ and $S_{a,i,t,m,m+1}$)
f_{aitmn} :	Number of life table births between exact ages a and $a+1$ to women age a , parity i , duration in parity t , and previous child deaths m and n

For the moment, we assume that the values of the partitioning factors Q_{aitm} have been calculated and are known.

The earlier equations (1) and (2) generate values of P_{aitmn} for specified values of the socioeconomic variables. After these probabilities are generated, then, in order to simplify the multidimensional life table equations that come later, the variables A and t are re-labeled by first replacing A with $a = (A-10)+(t-1) = A+t-11$, and then replacing t with $t-1$. Duration in parity t then starts at 0 instead of 1 (consistent with conventional demographic notation), and age in the multidimensional life table starts at 0 instead of 10. For example, the probability $P_{aitmn} = P_{27,4,3,1,1}$ is re-labeled as $P_{aitmn} = P_{19,4,2,1,1}$.

In the multidimensional life table, unlike the underlying CLL equations, duration in parity can be higher than 30 years for the 0–1 transition, and higher than 10 years for higher-order transitions, because everyone is followed from age 0 to age 40 (age 10 to age 50 before re-labeling). This is handled in the multidimensional life table by setting $P_{a,0,t,m,n} = 0$ when $t > 29$, and by setting $P_{aitmn} = 0$ when $i > 0$ and $t > 9$.

Formulae for the 0–1 transition are then

$$S_{0,0,0,0,0} = 1,000 \quad (\text{A.1})$$

$$S_{a,0,t,0,0} = S_{a,0,a,0,0} = S_{a-1,0,a-1,0,0}(1 - P_{a-1,0,a-1,0,0}) \quad \text{for } a > 0 \quad (\text{A.2})$$

$$f_{a,i,t,0,0} = S_{a,i,t,0,0} P_{a,i,t,0,0} \quad (\text{A.3})$$

Because there is no previous child mortality in the case of the 0–1 transition, m and n are both zero in the above equations.

Panel 1 of Figure 1 for the 1–2 parity transition, discussed earlier in the main text, shows how women progress by age, duration in parity, and child mortality state. Panel 1 of Figure A.1 shows the corresponding progression of survivors, starting with S_{aitm*} , where the asterisk indicates that the value of n can be either m or $m+1$. Panel 2 elaborates Panel 1 by partitioning S_{aitm*} into two groups, one consisting of women who do not experience a child death during the previous one-year age interval, and the other consisting of women who do experience a child death during the previous one-year age interval.

Formulae corresponding to Panel 2 of Figure A.1 for the 1–2 transition are:

If $t=0$:

$$S_{a,1,0,0,0} = \sum (S_{a,0,t,0,0} P_{a,0,t,0,0}) = \sum f_{a,0,t,0,0} \quad \text{where the summation is over } t \quad (\text{A.4})$$

$$S_{a,1,0,0,1} = 0 \quad (\text{A.5})$$

$$S_{a,1,0,1,1} = 0 \quad (\text{A.6})$$

If $t = 1$:

$$S_{a,1,1,0,0} = S_{a-1,1,0,0,0}(1 - P_{a-1,1,1,0,0})(1 - Q_{a,1,1,0}) \quad \text{for } a > 0 \quad (\text{A.7})$$

$$S_{a,1,1,0,0} = S_{a-1,1,0,0,0}(1 - P_{a-1,1,1,0,0})Q_{a,1,1,0} \quad \text{for } a > 0 \quad (\text{A.8})$$

$$S_{a,1,1,1,1} = 0 \quad (\text{A.9})$$

If $t = 2$:

$$S_{a,1,2,0,0} = S_{a-1,1,1,0,0}(1 - P_{a-1,1,1,0,0})(1 - Q_{a,1,2,0}) \quad \text{for } a > 0 \quad (\text{A.10})$$

$$S_{a,1,2,0,0} = S_{a-1,1,1,0,0}(1 - P_{a-1,1,1,0,0})Q_{a,1,2,0} \quad \text{for } a > 0 \quad (\text{A.11})$$

$$S_{a,1,2,1,1} = S_{a-1,1,1,0,1}(1 - P_{a-1,1,1,0,1}) \quad \text{for } a > 0 \quad (\text{A.12})$$

If $t > 2$:

$$S_{a,1,t,0,0} = S_{a-1,1,t-1,0,0}(1 - P_{a-1,1,t-1,0,0})(1 - Q_{a,1,t,0}) \quad \text{for } a > 0 \quad (\text{A.13})$$

$$S_{a,1,t,0,1} = S_{a-1,1,t-1,0,0}(1 - P_{a-1,1,t-1,0,0})Q_{a,1,t,0} \quad \text{for } a > 0 \quad (\text{A.14})$$

$$S_{a,1,t,1,1} = (S_{a-1,1,t-1,0,1})(1 - P_{a-1,1,t-1,0,1}) + (S_{a-1,1,t-1,1,1})(1 - P_{a-1,1,t-1,1,1}) \quad \text{for } a > 0 \quad (\text{A.15})$$

$$f_{aitmn} = S_{aitmn} P_{aitmn} \quad (\text{A.16})$$

Formulae for higher-order parity transitions follow the same logic, with the following exceptions: (1) When $t = 0$, one needs to add the number of births from the previous transition in order to determine how many women start the next transition in each mortality state. (2) More child mortality states are added as parity increases. See Eini-Zinab (2011) for details.

Once the multidimensional life table is constructed, the total fertility rate is calculated as

$$\text{TFR} = (\sum f_{aitmn}) / 1,000 \quad (\text{A.17})$$

where the summation is over a, i, t, m , and n . Formulae for PPRs, ASFRs, mean and median ages at childbearing, and mean and median birth intervals, which are also calculated from life table births f_{aitmn} , are straightforward and not shown.

Partitioning factor

Two approaches for calculating Q_{aitm} were tested. For ease of exposition, these two approaches are referred to here as the “overall probability approach” and the “logit model approach”. The overall probability approach uses the overall probability of failure (next birth) at age a , parity i , duration t , and number of previous child deaths m as part of the estimation procedure. The logit model approach regresses the difference between m and n (1 or 0) on age, parity, duration in parity, m , and the socioeconomic variables. This logit regression is run on the expanded data set for each parity transition separately. The fitted logit model yields a predicted proportion (i.e., a predicted value of the difference, $n-m$) of women who experienced a child death during the previous age interval for specified values of the predictor variables.

For reasons discussed shortly, the overall probability approach is preferred over the logit model approach. As an example, the overall probability approach is illustrated in Figure A.2 for the case where $S_{a,i,t,2*} = S_{a,i,t,2,2} + S_{a,i,t,2,3} = 100$ women. The problem is how to partition the $S_{a,i,t,2*}$ women into the two groups $S_{a,i,t,2,2}$ and $S_{a,i,t,2,3}$. To do this, we first define the overall probability of transition $P_{aitm\bar{n}}$ where $\bar{n}$ is the average number of previous child deaths at age a . In Figure A.2, $\bar{n}$ is a number between 2 and 3.

The following equations are generated from the figure:

$$S_{a,i,t,2*} = S_{a,i,t,2,2} + S_{a,i,t,2,3} \quad (\text{A.18})$$

$$S_{a+1,i,t+1,2*} = S_{a,i,t,2,2}(1 - P_{a,i,t,2,2}) \quad (\text{A.19})$$

$$S_{a+1,i,t+1,3*} = S_{a,i,t,2,3}(1 - P_{a,i,t,2,3}) \quad (\text{A.20})$$

It is assumed that

$$S_{a+1,i,t+1,2\bar{n}} = S_{a+1,i,t+1,2*} + S_{a+1,i,t+1,3*} \quad (\text{A.21})$$

Equation (A.21) states that the number of women who move to the next age and duration in parity, regardless of their child mortality state, equals the sum of the number of women who remain in child mortality state $m = 2$ and those who move to child mortality state $n = m+1 = 3$. When equations (A.18) and (A.21) are solved simultaneously, using elements from equations (A.19) and (A.20), the numbers of women $S_{a,i,t,2,2}$ and $S_{a,i,t,2,3}$ are

$$S_{a,i,t,2,2} = \frac{S_{a,i,t,2*}(P_{a,i,t,2,3} - P_{a,i,t,2\bar{n}})}{(P_{a,i,t,2,3} - P_{a,i,t,2,2})} \quad (\text{A.22})$$

$$S_{a,i,t,2,3} = \frac{S_{a,i,t,2*}(P_{a,i,t,2,2} - P_{a,i,t,2\bar{n}})}{(P_{a,i,t,2,2} - P_{a,i,t,2,3})} \quad (\text{A.23})$$

From equation (A.23) it is evident that the partitioning factor can be calculated as

$$Q_{a,i,t,2} = \frac{P_{a,i,t,2,2} - P_{a,i,t,2,\bar{n}}}{P_{a,i,t,2,2} - P_{a,i,t,2,3}} \quad (\text{A.24})$$

with $P_{aitm\bar{n}}$ estimated by substituting values of age A (where $A = a - t + 1$), t (where $t = t + 1$), m , and $\bar{n}$ into the CLL model equation for parity transition i to $i + 1$ (equation (1) or (2) in the main text). The value of $\bar{n}$, which is computed directly from the data, is specific for age a , parity i , duration t , starting child mortality state m , and values of the socioeconomic variables. For example, to estimate $P_{25,3,4,2,\bar{n}}$ one substitutes $A = 31$, $t = 5$, $D_1 = 2$, and D_2 equal to the computed value of $\bar{n}$ into the CLL equation for the 3–4 transition. Because the starting child mortality state in this example is 2, the mean of D_2 , specified by age, parity, starting child mortality state, and values of the socioeconomic variables, is a number between 2 and 3.

Formula (A.24) works well as long as the two probabilities in the denominator of the right side of the formula are not equal. When they are equal, the value of Q is undefined. In this case, which rarely occurs, the logit model approach is used to estimate Q .

Panel 1: Possible child mortality transitions within parity transition 1-2

Panel 2: Possible child mortality transitions within parity transition 2-3

Panel 3: Possible child mortality transitions within parity transition 3-4

Figure 1.

Possible child mortality transitions for a woman within parity transitions 1–2, 2–3, and 3–4

Notes: Child deaths pertain to children of any age. a denotes woman's age, and t denotes her duration in parity. In each of the three panels, it is assumed that the starting parity is attained at woman's age a , so that $t = 0$ at age a . $M_0, M_1, M_2, \dots$ are one-year-lagged child mortality states denoting the woman's number of previous child deaths at age $a-1$. For any particular woman, M_m and m are numerically identical; i.e., M_m is just another way of writing m .

Panel 1: Parity transition 1-2 (S_{a,i,t,m^*} not partitioned)

Panel 2: Parity transition 1-2 (S_{a,i,t,m^*} partitioned)

Figure A.1.

Elaboration of panels 1 of Figure 1

Note: For $t > 0$, S_{a,i,t,m^*} in panel 1 is partitioned into S_{aitmm} and S_{aitmn} (where $n = m + 1$) in panel 2. The asterisk in S_{a,i,t,m^*} indicates that the child mortality state at the end of the previous age interval (equivalently, at the start of the current age interval) can be either m or $m+1$.

Figure A.2.

Logic of the “overall probability approach” for calculating the partitioning factor

Table 1

Percentaged distribution of sample women by socio-economic variables included in the analysis

Predictor variable	Women age 45–49			Women age 10–49		
	NFHS-1	NFHS-2	NFHS-3	NFHS-1	NFHS-2	NFHS-3
Residence						
Urban	28	30	35	28	28	32
Rural	72	70	66	72	72	68
Education						
Illiterate	71	61	57	50	41	35
Low	16	17	16	26	23	22
High	13	22	26	24	36	43
Wealth Index						
Low	39	36	39	41	41	45
Medium	32	31	30	31	32	31
High	29	32	31	28	27	24
Religion						
Hindu	83	83	83	81	80	80
Other	17	17	17	19	20	20
SC/ST						
SC/ST	20	25	26	20	27	28
Other	80	75	74	80	73	72
Region						
North	36	33	35	36	36	38
East	25	25	25	26	26	27
South	25	29	26	23	24	21
West	15	14	14	14	15	14
No. of women	8,592	8,661	9,807	144,626	149,016	153,348

Source: International Institute for Population Sciences (IIPS) (1995); International Institute for Population Sciences (IIPS) and ORC Macro (2000); International Institute for Population Sciences (IIPS) and Macro International (2007).

Notes: NFHS-1 was conducted in 1992–93, NFHS-2 in 1998–99, and NFHS-3 in 2005–06. Women 45–49 are the basis of the cohort analysis. Women 10–49 are the basis of the period analysis. Numbers of missing cases are negligible except for the Scheduled Caste/Scheduled Tribe (SC/ST) variable in the NFHS-2 and NFHS-3 surveys; about 3 percent of women in these two surveys have missing information

on the SC/ST variable. The percentaged distributions exclude missing cases. The calculation of percentages incorporates individual-level weights as specified in each of the three surveys. In subsequent tables, weights are also used when fitting the underlying CLL models.

Table 2

TFR_{WCM}, TFR_{NCM}, mean number of child deaths per woman, child replacement rate, and mean age of women at child death: NFHS surveys

	NFHS-1	NFHS-2	NFHS-3
COHORT			
TFR _{WCM}	4.88	4.45	3.99
TFR _{NCM}	4.57	4.15	3.69
Δ TFR	0.31	0.30	0.30
<i>D</i>	0.94	0.72	0.55
<i>R</i>	0.33	0.42	0.55
Mean <i>A_d</i>	29.3	28.6	28.0
PERIOD			
TFR _{WCM}	3.13	2.77	2.65
TFR _{NCM}	2.98	2.65	2.57
Δ TFR	0.15	0.11	0.08
<i>D</i>	0.29	0.22	0.16
<i>R</i>	0.51	0.53	0.53
Mean <i>A_d</i>	28.4	27.9	28.2

Source: As for Table 1.

Notes: Δ TFR = TFR_{WCM} - TFR_{NCM}. Mean *A_d*s mean age of mother at child death, averaged over child deaths. All measures in this table are derived from multidimensional life tables based on CLL models in which the set of predictor variables includes age at starting parity *A*, duration in parity *t*, and variables *D₁*, and *D₂* representing number of previous child deaths at the start and end of the previous age interval. Socioeconomic variables are excluded from the set of predictor variables.

Table 3

Unadjusted and adjusted multidimensional life table estimates of the total fertility rate (TFR_{WCM}) and the child replacement rate (R): Cohort analysis, India's NFHS surveys

Predictor Variables	TFR _{WCM}			Replacement Rate (R)			
	NFHS			NFHS			
	1	2	3	1	2	3	
Residence							
Unadjusted	Urban	4.2	3.8	3.4	0.39	0.42	0.46
	Rural	5.1	4.7	4.3	0.31	0.40	0.54
Adjusted	Urban	4.6	4.1	3.9	0.27	0.34	0.40
	Rural	4.9	4.5	4.0	0.27	0.39	0.46
Education							
Unadjusted	Illiterate	5.2	5.0	4.6	0.28	0.36	0.47
	Low	4.5	4.2	3.7	0.31	0.42	0.47
Adjusted	High	3.3	3.2	2.8	0.39	0.39	0.38
	Illiterate	5.0	4.7	4.3	0.25	0.37	0.43
	Low	4.6	4.3	3.8	0.29	0.37	0.42
Wealth Index	High	4.4	3.8	3.3	0.34	0.37	0.38
	Low	5.4	5.0	4.8	0.27	0.35	0.44
Unadjusted	Medium	4.9	4.6	3.9	0.22	0.33	0.41
	High	4.1	3.7	3.1	0.44	0.48	0.53
Adjusted	Low	4.9	4.2	4.1	0.25	0.32	0.39
	Medium	4.9	4.5	3.9	0.22	0.31	0.38
Religion	High	4.6	4.3	3.7	0.34	0.48	0.52
	Hindu	4.8	4.3	3.9	0.35	0.44	0.58
Unadjusted	Muslim	5.9	5.8	5.1	0.18	0.46	0.33
	Hindu	4.8	4.3	3.9	0.28	0.38	0.46
Adjusted	Muslim	5.8	5.5	5.0	0.11	0.28	0.16
	SC/ST						

Predictor Variables		TFR _{WCM}			Replacement Rate (R)		
		NFHS			NFHS		
		1	2	3	1	2	3
Unadjusted	SC/ST	5.2	4.8	4.5	0.30	0.38	0.50
	Other	4.8	4.3	3.8	0.34	0.43	0.56
	Adjusted	4.9	4.2	4.1	0.26	0.38	0.41
Adjusted	SC/ST	4.9	4.2	4.1	0.26	0.38	0.41
	Other	4.8	4.4	3.9	0.27	0.37	0.45
Region							
Unadjusted	North	5.4	5.2	4.7	0.34	0.39	0.53
	East	5.0	4.6	4.3	0.28	0.43	0.48
	South	4.3	3.8	3.1	0.27	0.36	0.39
	West	4.5	3.8	3.4	0.31	0.40	0.43
Adjusted	North	5.2	5.0	4.6	0.29	0.34	0.43
	East	4.9	4.5	4.1	0.24	0.41	0.44
	South	4.4	3.9	3.2	0.23	0.35	0.41
	West	4.7	4.0	3.8	0.28	0.35	0.33

Source: As for Table 1.

Table 4

Unadjusted and adjusted multidimensional life table estimates of the total fertility rate (TFR_{WCM}) and the child replacement rate R Period analysis, India's NFHS surveys

Predictor Variables		TFR_{WCM}			Replacement Rate (R)		
		NFHS			NFHS		
		1	2	3	1	2	3
Residence							
Unadjusted	Urban	2.6	2.3	2.1	0.50	0.53	0.53
	Rural	3.4	3.0	2.9	0.48	0.50	0.50
Adjusted	Urban	3.1	2.7	2.5	0.46	0.48	0.56
	Rural	3.2	2.9	2.7	0.44	0.51	0.57
Education							
Unadjusted	Illiterate	3.8	3.5	3.5	0.43	0.42	0.41
	Low	2.9	2.8	2.7	0.48	0.55	0.63
	High	2.3	2.2	2.1	0.52	0.56	0.57
Adjusted	Illiterate	3.5	3.2	3.1	0.41	0.43	0.47
	Low	2.9	2.8	2.5	0.44	0.52	0.61
	High	2.9	2.6	2.5	0.52	0.53	0.63
Wealth Index							
Unadjusted	Low	3.7	3.3	3.3	0.42	0.40	0.41
	Medium	3.2	2.8	2.5	0.45	0.54	0.54
	High	2.4	2.1	1.9	0.49	0.57	0.57
Adjusted	Low	3.4	3.0	2.9	0.43	0.41	0.45
	Medium	3.1	2.7	2.5	0.45	0.53	0.54
	High	2.9	2.6	2.4	0.44	0.54	0.70
Religion							
Unadjusted	Hindu	3.1	2.7	2.6	0.53	0.54	0.55
	Muslim	4.0	3.3	3.2	0.42	0.48	0.45
Adjusted	Hindu	3.1	2.7	2.6	0.46	0.51	0.56
	Muslim	4.1	3.7	3.4	0.34	0.32	0.43
SC/ST							

Predictor Variables		TFR _{WCM}			Replacement Rate (R)		
		NFHS			NFHS		
		1	2	3	1	2	3
Unadjusted	SC/ST	3.5	3.0	3.0	0.45	0.44	0.52
	Other	3.0	2.7	2.5	0.52	0.56	0.52
	Adjusted	3.1	2.8	2.8	0.41	0.44	0.58
Region	Other	3.1	2.8	2.6	0.46	0.52	0.55
	North	3.8	3.4	3.1	0.52	0.53	0.47
	East	3.1	2.7	2.8	0.42	0.48	0.47
Adjusted	South	2.5	2.2	2.0	0.30	0.31	0.29
	West	2.8	2.6	2.3	0.48	0.46	0.59
	North	3.8	3.4	3.2	0.46	0.48	0.47
Adjusted	East	3.0	2.6	2.7	0.41	0.52	0.52
	South	2.7	2.4	2.2	0.41	0.46	0.54
	West	3.1	2.9	2.7	0.45	0.38	0.62

Source: As for Table 1.