International Journal of Innovation and Scientific Research
ISSN 2351-8014 Vol. 17 No. 1 Aug. 2015, pp. 77-90

http://www.ijisr.issr-journals.org/

Trends and Differentials of Teenage Birth in Ethiopia

Birhanu Worku and Eshetu Wencheko

College of Natural Sciences, Department of Statistics, Addis Ababa University,
P.O. Box 1176, Addis Ababa, Ethiopia

ABSTRACT: Globally, each year around 16 million girls aged 15-19 give birth, accounting for around 11 percent of all births. The main objectives of this study were to identify predictors of teenage birth and examine the trend of teenage birth based on data from three Ethiopian Demographic Surveys (EDHS) conducted in 2000, 2005, and 2011. Discrete-time hazard modeling was used to estimate the hazard of first birth before age 20 after controlling for the effects of socio-economic factors. The results suggested that the overall likelihood of first birth before age 20 among Ethiopia women decreased slightly over time in the three DH surveys. At individual level, women's education, especially secondary and higher, had a strong effect to delay first birth during adolescence in all three surveys. Residing in urban areas was inversely associated with teenage birth. Exposure to mass media has a significant delaying influence in the 2000 (28.6%) compared to 17.1% and 15.8% for the 2005 and 2011 EDHS, respectively.

KEYWORDS: Discrete-time, First birth, Hazard model, Person-Period Data, Teenage birth.

1 INTRODUCTION

Globally, each year around 16 million girls aged 15-19 give birth, accounting for around 11 percent of all births (WHO, 2008). Almost 95% of these births occur in developing countries. They range from about 2% in China to 18% in Latin America and the Caribbean. Half of all adolescent births occur in just seven countries: Bangladesh, Brazil, the Democratic Republic of Congo, Ethiopia, Nigeria, India and the United States (WHO 2008).

Countries of Latin America and the Caribbean and Sub-Saharan Africa have the highest proportion of adolescent births (UNICEF, 2012 report). Approximately 95 percent of adolescent births occur in low and middle-income countries (United Nations Department of Economic and Social Affairs, 2011). Bangladesh, India, and Nigeria alone account for one in every three of the world's adolescent births and the only industrialized country among the top 10 countries with the highest number of adolescent births is the United States (UNICEF, 2012).

Early childbearing is recognized worldwide to have a profound impact on the well-being and reproductive health of young women, as well as the overall pace and direction of a country's development (AGI, 1998). Early childbearing can derail a young woman's educational prospects, reduce her long-term social and economic autonomy, and endanger both her health and that of her newborn.

Compared to adult mothers, adolescent mothers are more likely to experience maternal mortality, anemia, and obstetric complications. In addition, their infants are at higher risk for preterm birth, low birth weight, poor nutritional status and fetal death. In poor countries, the health of women and children is also influenced by a range of social and economic factors such as the mother's education, access to health care services, decision-making power, acceptance of contraceptives, and employment opportunities (Gill, Pande and Malhotra 2007; Taffa and Obare 2004).

The major objectives of the study were to analyze trend and identify predictors of teenage birth in Ethiopia. Accordingly, we found it appropriate and relevant to assess the trends and characteristics of teenage birth from three nationally representative datasets based on the three 2000, 2005, and 2011 Ethiopian Demographic and Health Survey. It is hoped that such a study would inform policy related to maternal health issues and population, with special emphasis on teenage women.

2 DATA AND METHODOLOGY

DATA SOURCE

In this study data from the 2000, 2005, and 2011 Ethiopian Demographic and Health Survey (EDHS) have been used. The three surveys were conducted by the Central Statistical Agency (CSA) under the auspices of the Ministry of Health with the worldwide MEASURE DEMOGRAPHIC HEALTH SURVEY (DHS) project, a USAID-funded project providing support and technical assistance in the implementation of population and health surveys in countries worldwide. The primary objectives of the EDHS were to provide up-to-date information for planning, policy formulation, monitoring, and evaluation of population and health programs in the country.

The 2000 EDHS was the first of its kind to be conducted in the country. In that survey a nationally representative data set was obtained through interviews with 15,367 women aged 15-49 years. Among these 6,428 were aged 15-24. In the 2005 EDHS a total of 14,070 women were interviewed including 5,869 women aged 15-24. The 2011 DHS included 16, 515 women aged 15-49 of whom 6,857 were of age 15-24. Since the primary objective of this study is about the fertility behavior of the youngest cohort, we focused on female respondents aged 15-24 at the time of each of the surveys.

STUDY VARIABLES

The response variable of this study is "age at first birth before age 20" in completed years. We define y_{it} as a binary response (yes, no) to the event that woman *i* giving first birth at age *t* (*t*=15-19, in completed years). By convention y_{it} is set to 1 if the women has her first child at age *t*, and set it 0, otherwise. The phrases "age at first birth" and "time at first birth" are used interchangeably throughout this study.

The predictors (variables/factors) included in the model that are assumed to determine teenage fertility were:

a. Woman's religion: coded as Coptic Orthodox, Protestant, Muslim, and "Others". The last group included Catholics and followers of traditional beliefs.
b. Frequent media exposure: measured by asking respondents whether they watched television, listened to radio broadcast or read newspapers on weekly basis.
c. Woman's educational attainment: no education, primary, secondary and above.
d. Place of residence: urban, rural
e. Occupation refers to working status of women and or the type of job a woman was engaged in at the time of the survey. It is classified as: Not working (includes not paid work), agricultural worker, nonagricultural worker.
f. Region refers to the nine regional administrations and two city administrations of Ethiopia in which a woman was living at the time of the survey.

METHODS OF DATA ANALYSIS

DISCRETE-TIME HAZARD ANALYSIS

Births occur in the reproductive age 15-49 years, and in some exceptional cases outside this age. Thus, for the analysis of birth histories it is appropriate to use continuous-time models such as the Cox model. However, data about birth histories are typically collected via retrospective surveys in which a DHS is an example. In such surveys it is common practice to record dates in large grouped-time intervals such as months or years. The application of continuous-time models to grouped-time survival data is not recommended because of the problem of the possible large number of ties (i.e., more than one individual experiences an event at the same time). To overcome difficulties that continuous-time methods have with these grouped time data, alternative methods have been developed (Allison, 1982). A popular alternative is the discrete-time approach, where time is treated as though it were truly discrete (Myer, Hankey and Mantel, 1973; Brown, 1975).

Discrete time hazard modeling allows considerable flexibility in handling time-varying covariates (in particular, a woman's age) (Allison, 1982). Another advantage of discrete-time hazard modeling is that it allows fitting censored observations (that is, teenagers aged 15-19 who had not yet completed adolescence at the time of a survey), as well as women aged 20-24. The model is essentially a logistic regression model with the response variable being the log-odds of a women having had a first birth at age *t* (*t* = 15, 16, 17, 18, 19).

The discrete-time hazard probability is the conditional probability that an individual *i* will experience the event of interest at time t given that the individual has not experienced the event of interest in any earlier time intervals (Singer and Willett, 1993). That is:

$$h_i(t) = P(T_i = t | T \geq T_i) \tag{1}$$

In this setting of age at first birth, $h_i(t)$ is the probability that a teenager *i* gave first birth in year *t* given that she had not given birth before time *t*.

Inference methods for survival analysis allow for right censoring. A teenager is right censored at age *t* if the observation period ends before experiencing the event of interest (first birth in this case). Thus the observation period for this subject is not $T_i = t$, but rather $T_i > t$. The end of the observation period may be determined by the design of the survey. In this study since EDHS is a retrospective (a single interview) survey the observation period is ended by design at the day of the interview.

With right censoring, the observation about subject *i* is represented with an ordered pair (t_i, y_{it}), where t_i is the time recorded and y_{it} is an indicator of the occurrence of the event of interest. Thus y_{it}=1 means that t_i is uncensored ($T_i = t$), while y_{it} = 0 means that t_i is censored ($T_i > t$). The standard estimation methods for survival models use censored times under the assumption of non-informative censoring. Informally, censoring is non-informative when, conditionally on the observed covariates, the end of the observation period does not depend on the hazard.

We next include a set of *q* predictors to equation (1) that characterize individuals in the population. We denote the *q* predictors in time period *t* for the *i*th individual by the vector $X_{it} = (x_{1it}, x_{2it}, \ldots x_{qit})'$. The discrete-time hazard function for individual *i* in time period *t* with *q* predictors is given (see Singer and Willett, 1993) by:

$$h_i(t \mid x_{it}) = P(T_i = t \mid T_i > t, X_{1it} = x_{1it}, X_{2it} = x_{2it}, \ldots X_{qit} = x_{qit}) \tag{2}$$

The covariates can be time-invariant or time-varying. Time-varying covariates are extremely useful in building a proper model for the hazard, but they are rarely available in practice because of the difficulty to measure them accurately, especially in retrospective surveys. So, only time-invariant covariates were considered in this study.

STATISTICAL MODEL FOR DISCRETE-TIME HAZARD

Although equation (2) shows that the hazard depends on the vector of predictors, it does not specify the functional form of dependence. This section provides a description of a formal model of a hypothesized relationship between the population hazard probabilities and predictors.

The most popular choice to specify how hazard depends on time and the predictor variables is the logistic regression model (Cox, 1972; Myers, Hankey, and Mantel, 1973; Byar and Mantel, 1975; Brown, 1975; Thompson, 1977; Mantel and

Hankey, 1978; Allison, 1982; Singer and Willett, 1993). The model represents the log-odds of event occurrence as a function of predictors and also has the attributed of baseline profile risk and a shift parameter that captures the effect of the predictors on the baseline profile (Singer and Willett, 1993). Therefore our proposed population discrete-time hazard model is:

$$h_i(t) = \frac{1}{1+\exp[-\{(\alpha_1 A_{1it} + \alpha_2 A_{2it} + \ldots + \alpha_T A_{Tit}) + (\beta_1 X_{1it} + \beta_2 X_{2it} + \ldots \beta_q X_{qit})\}]} \quad (3)$$

Here A_{1it} , A_{2it} , …, A_{Tit} are a sequence of dummy variable, with values $(a_{1it}, a_{2it}, .. a_{Tit})$ indexing time period. α_1 , α_2 ,…, α_T are intercept parameters that capture the baseline level of hazard in each time period. The slope parameters β_1 , β_2 ,…, β_q describe the effects of the predictors on the baseline hazard function, albeit on a logistic scale (Singer and Willett, 1993). *T* refers to the last time period observed for anyone in the sample. If t_i represents the last time period when individual *i* was observed (and at which time she was either censored or experienced the target event), then *T*=sup {t_i}. Taking the logit transformation of both sides of (3) we obtain

$$\ln\left(\frac{h_i(t)}{1-h_i(t)}\right) = (\alpha_1 A_{1it} + \alpha_2 A_{2it} + \ldots + \alpha_T A_{Tit}) + (\beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_q X_{qit}) \ . \quad (4)$$

This form assumes that the predictors are linearly associated with the logistic transformation of hazard (logit-hazard), not with the hazard themselves, nor with the natural logarithm of the hazard probabilities.

We also notice that the discrete-time hazard model contains no single intercept, instead the alpha parameters act as multiple intercepts, one per time period. When the values of all the predictors X_1 , X_2 ,…, X_T are set zero, the population discrete-time hazard model depends only on α_1 , α_2 ,… α_T and represent the population baseline logit-hazard function because it captures the time-period by time-period conditioning log-odds that individuals whose covariate values are all zero (baseline group) will experience the event in each time period, given that they have not already experienced the event (Singer and Willett,1993).

ESTIMATION TECHNIQUE

Let y_{it} be a dichotomous indicator variable that female teenager *i* gave birth at time t. The coding here is that y_{it} is 0 if teenager *i* did not experience the event of interest at time *t* and y_{it} is 1, otherwise. There will also be instances when an individual does not experience the event of interest before the observation time ends, and those individuals must be censored. Let C_i be a dichotomous indicator variable that describes if an individual was censored or not with the coding c_i = 0 if individual *i* has not been censored and c_i = 1 if individual *i* has been censored.

The maximum likelihood method is used to estimate the parameters α_1 , α_2 ,…, α_T and β_1 , β_2 ,…, β_q in equations (3) and (4) thereby giving an estimate for $h_i(t)$. The likelihood function must be constructed in two parts because of censoring. The two parts of the likelihood function deal with first the uncensored individuals, that is, the probability that the individual experienced the event of interest at time t_i , and the censored individuals, that is, the probability that the individual experienced the event of interest after time period t_i .

That is the contribution of subject *i* to the likelihood is different if the time is uncensored or censored:

For uncensored ($y_i = 1$): $P(T_i = t_i) = \prod_{u=1}^{t_i - 1} [1 - h_i(u)] x h_i(t_i)$ (5)

For censored $(y_i = 0) : P(T_i > t_i) = \prod_{u=1}^{t_i} [1 - h_i(u)]$. (6)

Here t_i represents the last time period when individual i was observed.

Assuming that individuals in the sample are independent (given their $x_{1it}, x_{2it}, ..., x_{qit}$ values), the likelihood function is simply the product of the probabilities of observing the sample data, $P(T_i = t_i)$ in the case of uncensored individuals (c_i = 0) and $P(T_i > t_i)$ in the case the uncensored individuals (c_i = 1) we have the likelihood function:

$$L = \prod_{i=1}^{n} [P\{T_i = t_i\}]^{1-c_i} [P\{T_i > t_i\}]^{c_i} \tag{7}$$

Substituting (5) and (6) into (7), and taking logarithm we have

$$l = \sum_{i=1}^{n} \left[(1-c_i) \ln\left(\frac{h_i(t_i)}{1-h_i(t_i)} \right) + \sum_{t=1}^{t_i} \ln(1-h_i(t)) \right] \tag{8}$$

The event-history indicator Y_{it} can be used with equation (8), and we get:

$$\sum_{t=1}^{t_i} y_{it} \ln\left(\frac{h_i(t)}{1-h_i(t)} \right) = \begin{Bmatrix} \ln\left(\frac{h_i(t_i)}{1-h_i(t_i)} \right) when, c_i = 0 \\ 0, when, c_i = 1 \end{Bmatrix}$$

$$= \quad (1-c_i) \ln\left(\frac{h_i(t_i)}{1-h_i(t_i)} \right) \quad . \tag{9}$$

Substitute (9) into the first term inside the bracket of equation (8) eliminates the censoring indicator c_i from the log-likelihood function. Replacing it by the dichotomous realization of the event-history process y_{it} we have obtain:

$$l = \sum_{i=1}^{n} \left[\sum_{t=1}^{t_i} y_{it} \ln\left(\frac{h_i(t_i)}{1-h_i(t_i)} \right) + \sum_{t=1}^{t_i} \ln(1-h_i(t)) \right].$$

This can be rewritten as:

$$l = \sum_{i=1}^{n} \sum_{t=1}^{t_i} \left[\ln\left(\frac{h_i(t_i)}{1-h_i(t_i)} \right)^{y_{it}} + \ln(1-h_i(t)) \right]$$

Combining like terms and take the antilog we have:

$$L = \prod_{i=1}^{n} \prod_{t=1}^{t_i} h_i(t)^{y_{it}} (1-h_{it})^{(1-y_{it})} \tag{10}$$

Equation (10) is the likelihood function for the discrete-time hazard process in terms of the data, y_{it}, and the hazard probability parameters, $h_i(t)$.

Following Allison (1982), Brown (1975), and Laird and Oliver (1981), the equivalence of the likelihood functions of the discrete-time hazard model in (10) and independent Bernoulli trials model allows us to treat the N dichotomous observed values y_{it} as a collection of independent dichotomous variables with a hypothesized logistic dependence on predictors. They can be regarded as the values of the outcome variable in a logistic regression analysis of the time-period indicators and covariates X. This provides a simple method of obtaining maximum likelihood estimates of $\alpha_1, \alpha_2, ..., \alpha_T$, $\beta_1, \beta_2, ..., \beta_q$ and hence $h_i(t)$ using standard logistic regression analysis software (Singer and Willet 1993). Because computer software for conducting logistic regression analysis is so widely available, we will illustrate the fitting of hazard models via standard logistic regression approach, rather than via direct maximization of the likelihood in (10).

CONSTRUCTING THE PERSON-PERIOD DATA

In a typical data set, each person (case) has one record of data. Discrete-time survival analysis model (DTSAM) requires a person-period format; that is, each person may have a different number of records depending on the duration of observation. So, the first step to conduct DTSAM is to convert the data into a person-period data format. In the converted person-period data set, different cases may have a different number of records depending on how long it takes to experience the event (time to first birth). Therefore before we conduct discrete-time survival analysis we transform the standard one-person, one-record data set (the person-period data set) as shown in Table 1.

Table 1.Conversion of a person-level data set into a person-period data set

Person-level data set

ID	DURATION	CENSOR	Education
3686	18	0	0
5440	17	0	2
5560	19	1	1

Person-period data set

ID	PERIOD	A1	A2	A3	A4	A5	Education	y_{it}
3686	15	1	0	0	0	0	0	0
3686	16	0	1	0	0	0	0	0
3686	17	0	0	1	0	0	0	0
3686	18	0	0	0	1	0	0	1
5440	15	1	0	0	0	0	2	0
5440	16	0	1	0	0	0	2	0
5440	17	0	0	1	0	0	2	1
5560	15	1	0	0	0	0	1	0
5560	16	0	1	0	0	0	1	0
5560	17	0	0	1	0	0	1	0
5560	18	0	0	0	1	0	1	0
5560	19	0	0	0	0	1	1	0

BASELINE HAZARD MODELS

We begin by estimating a simple discrete-time hazard model using a standard logistic regression model that includes only a set of age dummy variables (A1 through A5, see Table 1) and no intercept model (Model 1, represented by equation (11)) as follows:

$$\psi_{it} = \ln\left(\frac{h_{it}}{1-h_{it}}\right) = \sum \alpha_t (AGE_{it}) \qquad (11)$$

where h_{it} is the hazard of giving first birth for person *i* at year *t*, and AGE_{it} is a dummy variable for age *t* for person *i*. The estimated coefficients of the α_i 's give the shape of the baseline logit-hazard curve (Reardon et al., 2002).

DISCRETE-TIME HAZARD MODEL WITH PREDICTORS

In the next model we add demographic covariates to model 1 in equation (11). Model 2 is represented by the following equation:

$$\psi_{it} = \sum \alpha_t (AGE_{it}) + \beta X_i \tag{12}$$

where X_i, is a vector of time-invariant covariates for teenager female *i*. Model 2 is used to estimate the effects of the demographic covariates on the logit-hazard curve (Reardon et al., 2002). We used this model to determine the effect of the demographic covariates on the hazard of first birth.

3 RESULTS

Descriptive Results. The life table (Table 2) illustrated the key components of the population hazard functions amongst the sample of women in the three surveys. The first column gives the age of women at first birth. The next three columns tally the number of women who did not give first birth at the beginning of each full year, the number who gave first birth at the age and the censored numbers. According to 2000 EDHS, 1,435 women had their first birth before age 20. Similarly, for 2005 and 2011 EDHS the figures were 1,361 and 1,466 respectively. For the same periods 4,248(77.16%), 4,281(75.88%) and 5,136(77.80%) were censored (did not give birth at the time of the interview).

The fifth column of Table 2 presented another summary – the proportion of women who gave first birth by the end of each full year. We note that among the 6,283 women, 2.94 % had their first birth at age 15 in 2000 survey and increased to 4% in 2005 and dropped down to 3.68% in the 2011 survey. Of the 2,453 women who did not give first birth by age 18, 11.25% gave their first birth at age 19 in the 2011 survey.

Table 2. Life table describing the distribution of event occurrence over time (age)

	Number of									Proportion					
	Women with no first birth at the beginning of each age (b)			Women who gave first birth during the age (a)			Were censored at age			Values in column (2) divided by the corr. values in column (1)			All women with no first birth at the end of each age		
Age	00	05	11	00	05	11	00	05	11	00	05	11	00	05	11
15	6283	5632	6602	185	226	243	826	683	879	0.0294	0.0401	0.0368	0.9706	0.9600	0.9632
16	5272	4723	5480	293	301	296	718	615	733	0.0556	0.0637	0.0540	0.9166	0.8987	0.9112
17	4261	3807	4451	350	316	339	567	516	603	0.0821	0.0830	0.0762	0.8413	0.8241	0.8418
18	3344	2975	3509	321	278	312	656	675	744	0.0960	0.0934	0.0890	0.7605	0.7471	0.7670
19	2367	2022	2453	286	230	276	2081	1792	2177	0.1208	0.1137	0.1125	0.6687	0.6621	0.6806

00, 05 and 11 stand for years 2000, 2005 and 2011, respectively.

Under the assumption of independent censoring we can use the sample hazard function to estimate the sample survival function at those ages when censoring precludes direct computation. For example, an estimate of the survival probability at the end of age 18 is 0.8418×(1-0.0890). In other words, the sample survival probability in any year is simply one minus the hazard probability for that year multiplied by the sample survival probability from the previous year. Accordingly, the sixth column of Table 2 presents the proportion of women who did not give first birth at the end of each full age. Examining this sample survival function showed that 97% of the women did not give first birth at age 15 in the 2000 survey. For the same age, 96% of the women did not give first birth in 2005. This figure has slightly increased in 2011 to 96.32%.

The plot of the population hazard function shows the hazard experienced by women in each time period (Figure 1). According to the left panel of the Figure 1, there was no clear difference of first birth probability at age 17 in the 2000 and 2005 surveys. We also note that there was no visible difference in the probability of not giving first birth at age 17 in the 2000 and 2011 surveys (right panel). But in the 2011 survey the probability was higher than in the two previous surveys after age 17. We also note that the probability in the 2005 survey was lower than in the other two surveys for all in the 15-19 years bracket.

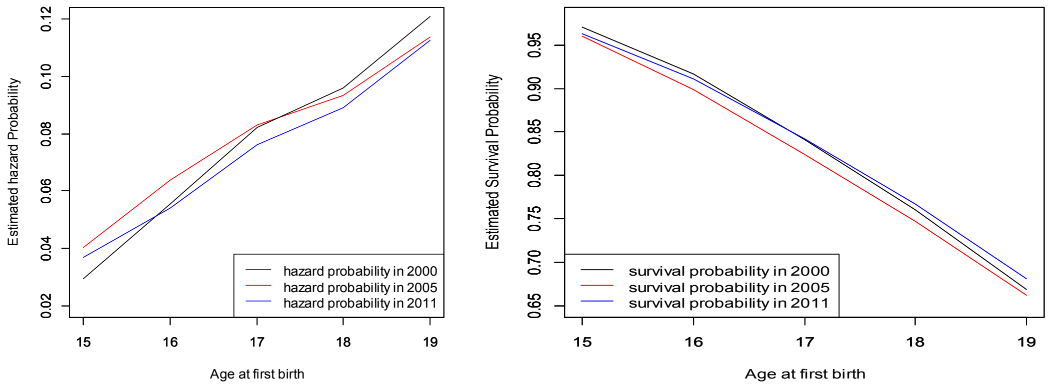

Figure 1. Estimates of survivor (did not give first birth before age 20) and hazard (did give first birth before age 20) probabilities for all women aged 15-24 at the time of interviews in each of the threeDHS

Results Of Discrete-Time Hazard Models. In order to fit the model, we need to restructure our data set, from what we refer to as a person-level data set, which contains one record for each person in the study, to a person-period data set, which contains one record for each time period that an individual is at risk of a giving first birth before age 20. Table 1 illustrates the conversion from a person-oriented data set to a person-period data set using three individuals as a illustration for the sample data from 2011 survey. A similar procedure was followed for 2000 and 2005 survey. The first two individuals have known age at first birth - the first woman gave first birth at age 18, and the second woman gave first birth at age 17. The third woman (ID5560) had not yet given birth; so she was censored at the end of age 19. The person-oriented data set describes a woman's event history using two variables: an event time (here DURATION, the period in which the individual experienced a first birth or was censored) and a censoring indicator (CENSOR = 0 for individuals who gave first birth and 1 for individuals who did not) and one time-invariant covariate, educational attainment of women (variable name: Education). The person-period data set includes a period variable, PERIOD, which specifies the time period *t* that the record describes. The particular time period described in the record is also identified through the set of time (age-at-first-birth) indicator variables (A1 through A5).

The person-period data set includes an event indicator, y_{it} , which indicates whether a first birth occurred at time *t* (0 = no, 1 = yes). For each person, the event indicator must be 0 in every record except the last. Non-censored individuals (like individual 3686) experience the event in their last period, whereas censored individuals never experience a first birth, so y_{it} remains 0 for all of their records (like in individual 5560).

Results Of Discrete-Time Hazard Model without predictors. Using equation (11), the first model to be fitted is a simple discrete-time hazard model with without any predictor and only a set age dummy variable (A1 through A5 as described in Table 1). That is a baseline model. Using dummy variables A1 to A5 equation (11) becomes:

$$\psi_{it} = \sum_{t=15}^{19} \alpha_t (AGE_{it}) = \alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5$$

where α_1 , α_2 , α_3 , α_4 , α_5 stand for α_{15} , α_{16} , α_{17} , α_{18} , α_{19} , respectively.

Table 3 gives estimates for Model 1 in equation (11).

Table 3. Parameter Estimates with standard errors and Fitted Hazard Probabilities from baseline discrete-time hazard model fitted to the 2000, 2005, and 2011 EDHS data

Parameter		Estimate ($\hat{\alpha}$) and the respective standard error in brackets			fitted hazard		
Period	predictor	2000	2005	2011	2000	2005	2011
15	A1	-3.4952*** (0.0746)	-3.1747*** (0.0679)	-3.2645*** (0.0654)	0.0294	0.0401	0.0368
16	A2	-2.8328*** (0.0601)	-2.6872*** (0.0596)	-2.8630*** (0.0598)	0.0556	0.0637	0.0540
17	A3	-2.4136*** (0.0587)	-2.4022*** (0.0587)	-2.4957*** (0.0565)	0.0821	0.0830	0.0762
18	A4	-2.2426*** 0.0889	-2.2723*** (0.0630)	-2.3270*** (0.0593)	0.0960	0.0934	0.0889
19	A5	-1.9846*** (0.0681)	-2.0530*** (0.0700)	-2.0653*** (0.0639)	0.1208	0.1137	0.1125

** * * p-value <0.001*

The parameter estimates for the time-indicator variables (A1 through A5) allow for the estimation of the risk of event at each year (from 15 to 19 year). Accordingly, the estimates $\hat{\alpha}_1$ through $\hat{\alpha}_5$ describe the shape of the overall fitted logit-hazard profile. That is, if the risk of event occurrence are unrelated to time, the hazard function would be flat and meaning that the $\hat{\alpha}s$ are approximately equal. If event risks increase over time, values of the $\hat{\alpha}s$ for later periods will be greater than for earlier periods which is identical to estimated hazard in Table 3. For example, in the 2000 EDHS (column 3), at age 15 we have $\hat{\alpha}_1 = -3.4952$ (s.e. = 0.0746) and the estimate of α_1 give an estimate of hazard $\hat{h}_1 = 0.0294$ (column 6). The interpretation is that a woman in the age group 15-24 has a risk of 2.94 percent of giving first birth at age 15 in 2000, which increased to 4.01 percent in 2005, and then decreased to 3.68 percent in 2011. For age 16, $\hat{\alpha}_2 = -2.8328$, $\hat{\alpha}_2 = -2.6872$, $\hat{\alpha}_2 = -2.8630$, in 2000, 2005 and 2011, respectively. Therefore, risks of giving first birth at age sixteen in 2000, 2005 and 2011, respectively, were 5.56, 6.37, and 5.4 percent showing the trend of first birth before age 20 in the three survey periods.

Results Of Discrete-Time Hazard Model with Covariates. The second model in this study was a discrete-time hazard model with demographic covariates (model 2 given in equation (12)). But before fitting this model a univariate discrete-time hazard model fit of each predictor variable was performed to select significant candidate predictor variables that would qualify for the multivariate discrete-time hazard model at a stringent 5% level. The results show that all predictors qualify for inclusion in the multivariate discrete-time hazard model.

A multivariable discrete-time hazard model containing region, religion, education, place of residence, occupation, and exposure to media information in addition to the age dummy variable A1, …, A5, was fitted for each of the three surveys.

The above consideration gives rise two to the full model

$$\psi_{it} = \alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5 + \beta_1 REG_i + \beta_2 EDU_i + \beta PLR_{3i} + \beta_4 MED_i$$
$$+ \beta_5 REL_i + \beta_6 OCC_i$$

The statistical analysis, however, showed that religion and occupation were not significant predictors at 5%. Hence model that excludes these two, namely

$$\psi_{it} = \alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5 + \beta_1 REG_i + \beta_2 EDU_i + \beta_3 PLR_i + \beta_4 MED_i$$

had to be considered. Further analysis showed that this reduced model provided a good fit at 5% level. Accordingly, model 2 (given by equation (12)) becomes:

$$\begin{aligned}\psi_{it} &= \sum_{t=15}^{19} \alpha_t (AGE_{it}) + \beta X_i \\ &= \alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5 + \beta_1 REG + \beta_2 EDU + \beta_3 PLR + \beta_4 MED\end{aligned} \quad (13)$$

Having achieved that we look for alternative re-parameterization of $\alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5$ in the above model. The reason for doing so is that the parameterization of the hazard profile using time indicators (A1 through A5, in this case) lacks parsimony and representation of the main effect of time requires the inclusion of many parameters in the discrete-time hazard model. Therefore, we need to adopt a particular algebraic form for the shape of the logit-hazard profile ($\alpha_1 A1 + \alpha_2 A2 + \alpha_3 A3 + \alpha_4 A4 + \alpha_5 A5$).

We note that the estimates of the parameter α_1 to α_5 in Table 3 which represents the population hazard probability in each time period under consideration showed that the hazard of first birth before age 20 was an increasing function of time.

A linear, quadratic, and cubic function of time (age at first birth or the indicator PERIOD in Table 1) were fitted. The plots of all functions are shown in Figure 2 below for the 2011 survey data. The same procedure was followed for 2000 and 2005 survey.

Using the difference in log likelihood value (-2 Log Likelihood) between the cubic and quadratic, linear and quadratic, we found that the quadratic function was a better fit than the cubic and linear.

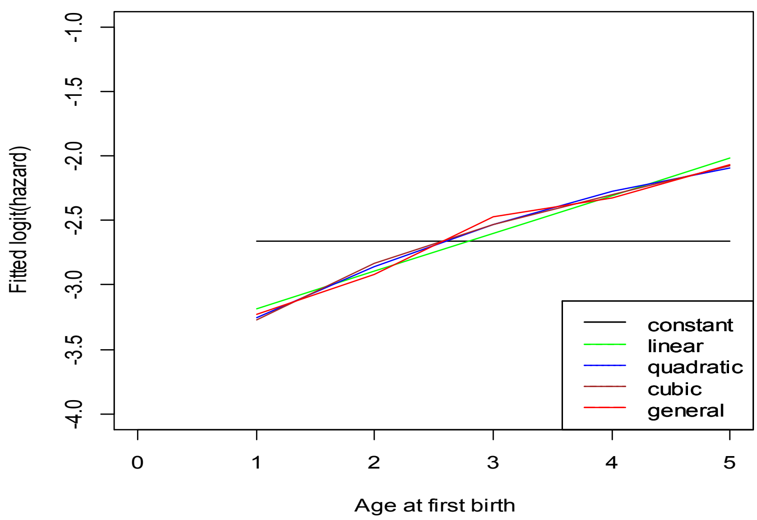

Figure 2: Fitted functions for the baseline model

As a result we have a the following model with a quadratic function of age at first birth:

$$\psi_{it} = Age + Age\_squared + \beta_1 REG_i + \beta_2 EDU_i + \beta_3 PLR_i + \beta_4 MED_i \quad (14)$$

where Age = age at first birth of woman, and Age_squared = square of age at first birth.

Further comparison of equations (13) and (14) revealed that the model (in equation (14)) provided appropriate fit to the data in all the three survey, meaning that it becomes our final model.

The results (estimated coefficient, standard error, and hazard of timing of first birth before age 20 among women age 15-24 years) in Table 4 are based on the final model above.

Table 4. Summary results of the discrete-time hazard model for women aged 15-24 for the three surveys

Variables	2000 Coeff.(SE)	HR	2005 Coeff.(SE)	HR	2011 Coeff.(SE)	HR
Intercept	-4.5122(0.1966)	-	-3.6123(0.1905)	-	-3.2360(0.1862)	-
Region						
Tigray	0.2279(0.1015)	1.256*	0.3421(0.1136)	1.408**	0.1722(0.1080)	1.188
Affar	0.0820(0.1240)	1.085	-0.1682(0.1452)	0.845	-0.2458(0.1188)	0.782*
Amhara	0.5032(0.0863)	1.654***	0.2030(0.0990)	1.225*	-0.2165(0.1077)	0.805*
Oromiya (ref.)	-	1.00	-	1.00	-	1.00
Somali	-0.3396(0.1393)	0.712*	0.0612(0.1519)	1.063	0.0459(0.1336)	1.047
Benishangul -Gumuz	0.1638(0.1121)	1.178	0.3613(0.1209)	1.435**	0.2450(0.1160)	1.278*
Gambel	-0.6721(0.1063)	0.511***	-0.2541(0.1053)	0.776*	-0.4389(0.1143)	0.645***
SNNP	0.1701(0.1241)	1.185	0.6089(0.1345)	1.838***	0.4466(0.1205)	1.563***
Harari	-0.1534(0.1290)	0.858	0.4408(0.1373)	1.554**	0.1898(0.1331)	1.209
Addis Ababa	-1.1047(0.1477)	0.331***	-0.4864(0.1528)	0.615**	-1.1653(0.1901)	0.312***
Dire Dawa	-0.9291(0.1560)	0.395***	0.2223(0.1528)	1.249	-0.1990(0.1456)	0.820
Woman's educational attainment						
No education (ref.)	-	1.00	-	1.00	-	1.00
Primary	-0.2941(0.0784)	0.745***	-0.5225(0.0747)	0.593***	-0.7456(0.0638)	0.474***
Secondary and above	-0.8820(0.1175)	0.414***	-1.3037(0.1156)	0.272***	-1.9242(0.1286)	0.146***
Woman's place of Residence						
Urban (ref.)	-	1.00	-	1.00	-	1.00
Rural	0.3429(0.0865)	1.409***	0.4273(0.1020)	1.533***	0.3351(0.0861)	1.398***
Exposure to media						
Yes	-0.3365(0.0693)	0.714***	-0.1879(0.0704)	0.829**	-0.1717(0.0626)	0.842**
No (ref.)	-	1.00	-	1.00	-	1.00

*p<=0.05;**p<=0.01;***p<=0.001; SE: standard error; HR: hazard ratio; ref.: reference

According to Table 4, the effect of region on the hazard of timing of teenage birth was not consistent across regions and over time. For example, a 15-20 year old woman who lived in Tigray in 2000 and 2005 had, respectively, 25.6 % (HR=1.256) and 40.8% (HR = 1.408) higher risk of having a first birth before 20 years of age compared to her counterpart in Oromiya region, controlling the effect of other variables in the model. On the other hand, the hazard of timing of first birth before age 20 was significantly lower in the three survey for Amhara region compared to Oromiya when the effect of other factors in the model were controlled.

Women with secondary and above level of education had the lowest chance of having a teenage first birth compared to women who had no education and the decrease was more pronounced in 2011. Similarly, women who had exposure to media information were less likely to have early birth compared to those who had no exposure to media news/information.

4 Discussion

The result of this study regarding the impact of education on early first birth agrees with the findings of others as discussed next. Findings of studies done in Brazil (Gupta and Leite, 1999) and in other eight sub-Saharan African countries (Gupta and Mahy, 2003) showed that high level of education was found to be strongly associated with delayed childbearing among adolescents. More specifically, Gupta and Mahy (2003) found that education (grade 8 and above) consistently and significantly helped to reduce the risk of having first birth before age 20. Kamal (2012) showed that secondary and higher level of education was an important determinant in delaying birth among women in Bangladesh. Another study in Bangladesh by Nahar and Min (2008) showed that higher education was inversely related to have first birth before age 20. A study in Sweden by Olausson et al. (2001) also revealed that teenage birth was positively associated with low educational attainment. According to Elisa and Nunez (2001) education showed a strong negative effect on teenage birth, especially up to 11-13 years of education in the six Latin American countries under study (Bolivia, Brazil, Colombia, Guatemala, Dominican Republic and Peru). The risk of having first birth before age 20 among 11-13 years of education was lower than the risk observed among those with 0-3 years of education.

In the 2000, 2005, and 2011 EDH the risk of having first birth before age 20 among for women exposed to media were 28.6%, 17.1% and 15.8%, respectively. These percentages show that the changes, especially for 2005 and 2011, are not dramatic. Perhaps, this could be because the increase in mass media exposure is a recent phenomenon, and that it takes time for media exposure to bring about increase in knowledge about teenage birth. A study by Gupta and Mahy (2003) conducted in eight sub-Sahara African countries agrees with the result of the current study. They found that regular listening to radio broadcast habit was inversely associated with the probability of an adolescence first birth in Cote de Voire and Zimbabwe.

The current study identified place of residence as a characteristic that is associated with adolescent motherhood. Urban women had a lower proportion of teenage birth than rural women of the age group 15-19. The studies by Gupta and Mahy (2003), Katherine et al. (2009), Chandrasekhars (2010), and Kamal (2012) came up with similar conclusions. A reason for that could be that women in urban areas had better access to health services than those living in rural places (World Bank, 2004). On the other hand, results from studies from Brazil and Colombia contradict our finding indicating that place of residence had no significant effect or loses its effect when the disparity in socio-economic levels was controlled (Gupta and Leite, 1999; Cesare and Rodriguez, 2006).

5 Conclusion

In this study, we were not only interested in 'whether' a woman had first birth before age 20, but also in 'when' they had first birth (age at first birth). The result of baseline model revealed that the chance of having first birth at age 15, 16, 17, 18, and 19 was increasing in all three surveys (Table 2). The study also revealed that residing in urban areas and having secondary and above level of education were inversely associated with teenage birth in all three surveys. Exposure to media did not show a considerable effect towards reducing teenage birth over time. Hence, more should be done to effectively use media information about early birth.

References

[1] Alan Guttmacher Institute (AGI, 1998). Into a New World: Young Women's Sexual and Reproductive Lives, New York.

[2] Allison, P.D. (1982). Discrete-time methods for the analysis of event histories. American Sociological Association, 13: 61-98.

[3] Brown, C.C. (1975). On the use of indicator variables for studying the time dependence of parameters in a response-time model. Biometrics 31: 943-947.

[4] Byar, D. P. and Mantel, N. (1975). Some interrelationships among the regression coefficient estimates arising in a class of models appropriate to response-time data. Biometrics 31: 943-947.

[5] Cesare, Mariachiara, and Rodríguez, Jorge Vignoli (2006). Micro analysis of adolescent fertility determinants: the case of Brazil and Colombia Papeles de población no. 48 cieap/uaem.

[6] Chandrasekhar, S. (2010). Factors affecting age at marriage and age at first birth in India. Journal of Quantitative Economics, 8(2).

[7] Cox, D.R. (1972). Regression models and life tables. Journal of the Royal Statistical Society, Series B, 34: 187-202

[8] Elisa,C.F. and Nunez, J. (2001). Teenage childbearing in Latin American countries. Latin American Research Network, No. 434.

[9] Gill, K., Pande, R. and Malhotra, A. (2007). Women deliver for development. The Lancet 370: 1347-1357.

[10] Gupta, N. and Leite, I.C. (1999). Adolescent fertility behavior. Trends and determinants in Northeastern Brazil. International Family Planning Perspectives 25(3):125-30.

[11] Gupta, N and Mahy, M. (2003). Adolescent childbearing in sub-Saharan Africa: Can increased schooling alone raise ages at first birth? Demographic Research 8(4): 93-106.

[12] Kamal, M. (2012). Adolescent motherhood in Bangladesh: Evidence from 2007 BDHS data. Canadian Studies in Population 39: 63-82.

[13] Katherine, C.L. , Prata, N. and Stewart, C. (2009). Adolescent childbearing in Nicaragua: A quantitative assessment of associated factors. International Perspectives on Sexual and Reproductive Health 35(2).

[14] Laird, N. and Oliver, D. (1981). Covariance analysis of censored survival data using log-linear analysis techniques. Journal of the American Statistical Association 76: 231-240.

[15] Mantel, N. and Hankey, B. (1978). A logistic regression analysis of response time data where the hazard function is time dependent. Communications in Statistics - Theory and Methods, 333-347.

[16] Myer, S.M., Hankey, B. and Mantel, N. (1973). A logistic exponential model for use with response-time data involving regressor variables. Biometrics 29: 257-269.

[17] Nahar, Q and Min, H. (2008). Trends and determinants of adolescent child bearing in Bangladesh. Macro International Inc.

[18] Olausson, P.O., Haglund, B., Weitoft, G.R. and Cnattingius, S. (2001). Teenage childbearing and long-term socioeconomic consequences: a case study in Sweden. Department of Medical Epidemiology, Karolinska Institutet, Stockholm, Sweden.

[19] Reardon, S.F, Brennan, R.T. and Buka, S.L. (2002). Estimating multi-level discrete-time hazard models using cross-sectional data: neighborhood effects on the onset of adolescent cigarette use. Multivariate Behavioral Research 37(3): 297-330.

[20] Singer, J.D. and Willett, J.B. (1993). It's about using discrete-time survival analysis to study duration and the timing of events. Journal of Educational Statistics 18(2): 155-195.

[21] Taffa, N. and Obare, F. (2004). Pregnancy and child health outcomes among adolescents in Ethiopia. Ethiopian Journal of Health Development 18 (2).

[22] Thompson, W. A., Jr. (1977). On the treatment of grouped observations in life studies. Biometrics 33:463-470.

[23] United Nations Department of Economic and Social Affairs, Population Division, '2011 Update for the MDG Database: Adolescent birth rate', POP/DB/Fert/A/MDG 2011, reanalyzed by UNICEF.

[24] United Nations Children's Fund (2012). Progress for Children. A report card on adolescents. No 10.

[25] World Bank (2004). Ethiopia: A Country Status Report on Health and Poverty. The World Bank Africa Region Human Development & Ministry of Health Ethiopia.

[26] World Health Organization (2008). Department of Making Pregnancy Safer, Adolescent Pregnancy.