Determinants of Desire for Children: A Multinomial Logistic Regression Approach

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Abstract: World population is a serious dilemma that is growing very fast. Most of the current global crises are the consequences of overpopulation. Overpopulation can result from growth rates driven by high fertility rates. Most of alarming growths are occurring in some Asian countries including Bangladesh. Recent trend of fertility decline in Bangladesh is not enough to attain stable population. The aim of this study is to isolate potential determinants of desire for more children and provide recommendations to eradicate them and accelerating fertility decline to achieve replacement level. Multinomial logit approach efficiently determined few key covariates namely child's sex preference, professional status, wealth index and residential places of women that are significantly associated with high fertility. Since the potential covariates marked here largely depend on female literacy. Thus the policy makers should pay their attention to ensure the female education and involve them in the workforce to enhance women's status. Female literacy can reduce poverty and discrimination between sons and daughters to eliminate societal attitudes toward sex preference and resume the further fertility decline.

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1. Introduction

The world population has experienced continuous growth since the mid of last century and raises concern about whether Earth is facing overpopulation. The population of the world will soon reach at a level where there will not be enough resources to sustain life, even though, the growth rate declined from 2.2 percent to 1.1 percent by 2009 since mid of the last century. Under the current rate, different projections show a steady decline in the population growth, with the expected population to reach between 8 and 10.5 billion between the year 2040 and 2050. The scientific consensus is that the current population expansion and accompanying increase in usage of resources are linked to threats to the ecosystem, such as rising levels of atmospheric carbon dioxide, global warming, and pollution. The Intergovernmental Panel on Climate Change has supported the scientific conclusion that human-caused increases in concentrations of greenhouse gases in the atmosphere are very likely the cause of most of the temperature increases in the world (UNFPA, 2009). Besides, in the last decade food production from both land and sea has declined relative to population growth. The area of agricultural land has shrunk, both through soil erosion and reduced possibilities of irrigation. The availability of water is already a constraint in some overpopulated countries. These are the warnings that the Earth is finite, and the natural systems are being pushed ever closer to their limits. In a nutshell, overpopulation and most of the social problems go hand in hand in today's society.

Among the Continents, Asia alone accounts for over 60 percent of the world population among which China and India together have about 40 percent of the world population. Bangladesh is a small country in South Asia with area 144,000 square kilometers. It has the highest population density in the world except few smaller countries. Population of Bangladesh is about more than 162 million in 2009 and contributes 2.36 percent of the world population and made it seventh most populous country in the world with growth rate 1.29 percent (WDI, 2010). There was an impressive decline in fertility in Bangladesh until 1980s. Unfortunately, it began to plateau during the 1990s and then resumed its nominal decline during the early 2000s. The average number of children per woman in Bangladesh has declined from 6.6 in the early 1970s to 2.7 children per woman today (UNFPA, 2009). In order to achieve a stable population, the current decline in fertility rate is not enough to reach at a replacement level fertility. So further research should be needed to isolate the risk factors or determinants of desire for more children and effective steps should be taken to eliminate or minimize those factors.

Logistic regression is frequently used to express the relationship between a binary response outcome and a set of explanatory variables. In practice, a number of situations occur where the outcome variable may have more than two levels. Binary logistic regression model can be easily generalized to handle the case where the outcome variable is nominal with more than two levels. Such logistic regression can be employed by means of a polychotomous or multi-category logistic regression model. Polychotomous logistic regression models are used in many fields. For instance, in demography, a researcher may wish to relate a respondent's choice of plan to desire for children to the respondent's age, place of residence, professional status, wealth index, sex preference and several other potential covariates. The goal is to model the odds of plan choice as a function of the covariates and to express the results in terms of odds ratios for choice of different plans. Such problem can be modeled with a nominal polychotomous or multinomial logistic regression, because the outcome categories are purely qualitative and not ordered in any way (Hosmer and Lemeshow, 2000; Kutner *et al.,* 2005).

Statistical techniques for the analysis of several discrete choices have been used with increasing regularity in social sciences and demographic analyses. Many problems in social sciences and demography involve a nominal dependent variable having more than two categories with a mixture of discrete and continuous independent variables. When the outcome variable is nominal having several categories with mixture of discrete and continuous explanatory variables, the traditional regression analysis, discriminant analysis and log-linear analysis are inappropriate to isolate the determinants those are responsible to influence the outcome. In such a case the application of one of a class of techniques referred to as discrete choice model (McFadden, 1974) is required. Multinomial logit analysis is one such statistical technique for relating a set of continuous or discrete covariates to a categorical outcome variable (Long, 1987; Bull and Donner, 1987; Hoffman and Duncan, 1988). Therefore, multinomial logit model is used to analyze the choice of an individual among a set of more than two alternatives and detects the risk factors responsible to influence the outcome variable.

The purpose of this study is to understand the multinomial logit model that uses maximum likelihood estimator and its application on desire for children and identify perfectly the determinants those are significantly responsible for the extra desire for children among the respondents. The goal of this article is to find out the reason of plateauing fertility decline and make recommendations to revise the policy of national family planning programs and its strategies to ensure that Bangladesh will reach at replacement level fertility within shortest time period.

2. Material and Methods

The Bangladesh Demographic and Health Survey (BDHS, 2007) is a part of the global Demographic and Health Surveys program, which is designed to collect data on fertility, family planning, and maternal and child health to serve as a source of population and health data for policymakers, program managers, and the research community. The BDHS was implemented through a collaborative effort with technical assistance provided by Macro International, USA and the financial support for the survey was provided by the United States Agency for International Development (USAID) under the authority of National Institute of Population Research and Training (NIPORT) of the Ministry of Health and Family Welfare, Bangladesh. The survey utilized a multistage cluster sample based on the Bangladesh census 2001. The survey was conducted since 24 March to 11 August, 2007 and the data was published for the research community on March, 2009. A total of 10819 households were selected for sample, of which 10400 were successfully interviewed. In those households, 11178 women were identified as eligible under reproductive age for the individual interview and interviews were completed for 10996 of them. But in this analysis, only 2357 eligible women having two living children and able to bear and desire more children are considered on the eve of global two children family campaign.

In the current study, the respondent's desire for more children has three options such that desire next child within two years as option 1, desire after two years as option 2 and desires no more child as option 3 which is the discrete choice outcome variable Y. The aim of this study is to determine the impact of respondent's place of residence (X_1), occupational status (X_2), wealth index (X_3) and sex preference (X_4) as potential covariates on Y. Place of residence X_1 is coded 0 for 'urban' and 1 for 'rural', occupational status X_2 is coded 0 for 'house wife' and 1 for 'professional', wealth index X_3 is coded 0 for 'middle class and rich' and 1 for 'poor' and sex preference X_4 is coded 0 for 'do not prefer child's sex' and 1 for 'prefer child's sex'.

2.1 Formulation of Multinomial Logit Model

Multinomial logistic regression is the extension of the binary logistic regression when the categorical dependent outcome has more than two levels. In order to develop a multinomial logistic regression model for a discrete outcome variable with more than two levels, the researcher should pay attention to the measurement scale. The problem under study is a multinomial logistic regression model for the case in which outcome is nominal scale. The simple approach to multinomial data is to nominate one of the response categories as a baseline or reference cell, calculate logit or log-odds for all other categories relative to the baseline, and then the logit be a linear function of the covariates.

Suppose the multi-response outcome variable be denoted as Y having number of response categories $J > 2$ and there exist n independent observations in the random sample. For the ith observation, without loss of generality, J binary response variables $Y_{i1}, Y_{i2}, ..., Y_{iJ}$ can be easily generated as

$$Y_{ij} = \begin{cases} 1 & \text{if the response is in category } j \\ 0 & \text{otherwise} \end{cases}$$

Since only one category can be selected for response i and it is obvious that $\sum_{j=1}^{J} Y_{ij} = 1$ (1)

For the J response categories, there are ${}^{J}C_2 = J(J-1)/2$ possible pairs of categories, and hence $J(J-1)/2$ linear predictors or logit functions can be constructed. Fortunately, it is not necessary to develop all possible logistic regression models. One category should be chosen as the baseline or referent category, and all other categories can be compared to it. The choice of baseline or referent category is arbitrary. Traditionally the last category is chosen as referent category, and this is usually the default choice for most but not all statistical software packages. Again let there are p covariates and an intercept term, represented by the vector X of length (p+1) with X_0=1. A general expression for the conditional probability of jth outcome category given the covariate vector is defined as

$$\theta_{ij} = P\left[Y=j|X\right] = \exp\left(X_i'\beta_j\right) \Big/ \sum_{k=1}^{J} \exp\left(X_i'\beta_k\right) \quad ;j=1,2,\cdots;J \qquad (2)$$

Using category J to denote the baseline category, only (J-1) comparison to the referent category can be done. The logit or log-odds for the jth such comparison is defined as

$$g_j(X) = \ln\left[\frac{P(Y=j|X)}{P(Y=J|X)}\right] = \beta_{j0} + \beta_{j1}X_1 + \cdots + \beta_{jp}X_p = X_i'\beta_j; \; j=1,2,\cdots,(J-1) \qquad (3)$$

The multi-response logit model presented in equation (3) is analogous to a binary logistic regression model, except that the probability distribution of the outcome is multinomial instead of binomial and we have J-1 equations instead of one. The J-1 multinomial logit equations contrast each of categories 1, 2, J-1 with category J. By means of (J-1) logits defined in equation (3), any other comparisons can be obtained easily and it is possible to obtain the (J-1) direct expression for the category probabilities in terms of the (J-1) linear predictors $X'\beta_j$. The conditional probabilities of each outcome category given the covariate vector $P(Y=j|X)$ for j=1, 2…J is a function of the vector of (J-1) × (p+1) parameters $\beta' = (\beta_1', \beta_2', \cdots, \beta_{J-1}')$ with $\beta_0 = 0$ and $g_J(X) = 0$. Under this restriction, equation (2) can be rewrite in terms of linear predictor as

$$\theta_{ij} = \exp\left(X_i'\beta_j\right) \Big/ 1 + \sum_{k=1}^{J-1} \exp\left(X_i'\beta_k\right); \; j=1,2,\cdots,(J-1) \qquad (4)$$

The next step is to describe the methods for obtaining estimates of the (J-1) parameter vectors $\beta_1, \beta_2, \cdots, \beta_{J-1}$ .There are two approaches commonly used for obtaining estimates of the parameter vectors, both employ maximum likelihood estimation. With the first approach, distinct binary logistic regressions are carried out for each of the (J-1) comparisons to the referent category. This approach is especially useful when proper statistical software program is not available for multi-response logistic regression (Begg and Gray, 1984).

A more accurate and efficient approach from a statistical viewpoint is to estimate the (J-1) logits simultaneously. In order to estimate the vectors of parameters, the likelihood for the full data set is required. To construct the likelihood function, J binary variables Y_{ij} (i=1,2,…,n and j=1,2,…,J) coded 0 or 1 are created to indicate the group membership of an observation. Theoretically, these binary variables are introduced only to clarify the likelihood function and are not used in the actual multinomial logistic regression analysis (Hosmer and Lemeshow, 2000; Kutner *et al.,* 2005). It is noted that no matter what value the outcome variable Y takes on, the sum of these variables is $\sum_{j=1}^{J} Y_{ij} = 1; \; \forall i$. Under such condition and J categories for the outcome variable Y, the conditional likelihood function for a sample of n independent observations is

$$l(\beta) = \prod_{i=1}^{n} P(Y_i = 1|X) = \prod_{i=1}^{n}\left[\prod_{j=1}^{J}\left[\theta_{ij}\right]^{Y_{ij}}\right] \qquad (5)$$

In order to obtain the log-likelihood function from equation (5), taking natural logarithm and using the fact that $\sum_{j=1}^{J} Y_{ij} = 1$, let $\theta_{iJ} = 1 - \sum_{j=1}^{J-1}\theta_{ij}$ and $Y_{iJ} = 1 - \sum_{j=1}^{J-1} Y_{ij}$ follows

$$L(\beta) = \sum_{i=1}^{n}\left(\sum_{j=1}^{J-1} Y_{ij} \ln\left[\theta_{ij}/\theta_{iJ}\right] + \ln\left[1 - \sum_{j=1}^{J-1}\theta_{ij}\right]\right) \qquad (6)$$

Using the results of equation (3) and (4) in (6), the log-likelihood function is

$$L(\beta) = \sum_{i=1}^{n}\left(\sum_{j=1}^{J-1}\left(Y_{ij}X_i'\beta_j\right) - \ln\left[1 + \sum_{j=1}^{J-1}\exp\left(X_i'\beta_j\right)\right]\right) \qquad (7)$$

The maximum likelihood estimates of the vectors of parameters $\beta_1, \beta_2, \cdots, \beta_{J-1}$ are those values of $\hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_{J-1}$ that maximize equation (7). The likelihood equations are found by taking the first partial derivatives of L (β) with respect to each of the unknown parameters and the maximum likelihood estimator $\hat{\beta}$ is obtained by setting these equations equal to zero and solving for β. Mathematically, the likelihood equations are

$$\partial L(\beta)/\partial\beta_{kj} = \sum_{i=1}^{n} X_{ik}\left(Y_{ij} - \theta_{ij}\right) \qquad (8)$$

for j = 1, 2, … ,(J-1) and k = 0,1,2, …, p with X_{i0} =1 for each observation. The solution requires the iterative computation and need a standard statistical software program to obtain these estimates. The (J-1) fitted response functions can be obtained by substituting the maximum likelihood estimates of the (J-1) parameter vectors into the equation (4) as

$$\hat{\theta}_{ij} = \exp\left(X_i'\beta_j\right) \Big/ 1 + \sum_{k=1}^{J-1} \exp\left(X_i'\hat{\beta}_k\right) \qquad (9)$$

The matrix of second partial derivatives is required to get the information matrix and the estimator of the covariance matrix of the maximum likelihood estimator. The general form of the elements in the matrix of second partial derivatives is given in equation (10) and equation (11) respectively for j and $j' = 1,2,\cdots,(J-1)$ and k and $k' = 0,1,2,\cdots,p$.

$$\partial^2 L(\beta)/\partial\beta_{kj}\partial\beta_{k'j} = -\sum_{i=1}^{n} X_{ik}X_{ik'}\theta_{ij}\left(1-\theta_{ij}\right) \qquad (10)$$

$$\partial^2 L(\beta)/\partial\beta_{kj}\partial\beta_{k'j'} = \sum_{i=1}^{n} X_{ik}X_{ik'}\theta_{ij}\theta_{ij'} \qquad (11)$$

The observed information matrix, say $I\left(\hat{\beta}\right)$, is the ($J$-1) ($p$+1) × ($J$-1) ($p$+1) matrix whose elements are the negatives of the values obtained from the equations (10) and (11) enumerated at $\hat{\beta}$. The estimator of the covariance matrix of the maximum likelihood estimator denoted as $v\left(\hat{\beta}\right)$, is the inverse of the observed information matrix, given by $v\left(\hat{\beta}\right) = I\left(\beta\right)^{-1}$.

3. Findings and Interpretation

In order to introduce the principal findings in the current study, suppose there are J=3 categories in the outcome variable and the third category is considered as referent category. In order to make inferences about the fitted model, various regression diagnostics similar to binary logistic regression should be examined because logistic regression model having polychotomous outcome categories make this a more complicated than was the case for binary logistic regression. It is evident that assessing the fit and monitoring logistic regression diagnostics using the (J-1) individual binary logistic regressions worthwhile (Kutner *et al.,* 2005). Hence, assessment of goodness-of-fit of the two binary logistic regression models were done separately through different summary measures of fit including Hosmer-Lemeshow test (Lemeshow and Hosmer, 1982) for goodness of fit and no extreme departure was found (results are beyond the scope of the study).

The SPSS 15.0 for Windows Evaluation Version, multinomial logistic regression output is presented in Table 1. It also indicates that the outcome variable contains three categories 1, 2, 3 and the last category as baseline. The other two categories is compared to it and presented them as Logit 1 and Logit 2 respectively. Table 1 exhibits the estimated regression coefficients $(\hat{\beta})$, estimated approximate standard errors $S.E(\hat{\beta})$, the Wald test statistics with degrees of freedom and p-values, the estimated odds ratios for the two estimated logits and the 95 percent confidence intervals for the odds ratios.

After estimating the coefficients, the next step is to throw lights on the fitted model commonly concerns an assessment of the significance of the covariates in the model. This usually involves formulation and testing of a statistical hypothesis to determine whether the covariates in the model are significantly associated to the outcome variable. Traditionally, a Wald test is one of the ways of testing the statistical significance of particular covariate in the model. The null hypotheses $H_0 : \beta_i = 0;\ i = 1,2,\cdots,8$ may be formulated for both logits and under the null hypothesis; the test statistic $W = \left[\hat{\beta}_i\right]^2 \Big/ \left[S.E\left(\hat{\beta}_i\right)\right]^2$ yields a chi-square distribution with single degree of freedom. All Wald tests presented in Table 1 having p-values are less than 0.05 indicating that all the covariates contribute significantly to predict the outcome variable and should be retained in the model. In all cases the direction of the association between the covariates and the estimated logits are indicated by the signs of the estimated regression coefficients and are fully expected patterns. However, several authors have identified problems with the use of the Wald statistic and generally it behaved in an aberrant manner often failing to reject the null hypothesis when the coefficient was significant (Hauck and Donner, 1977; Agresti, 2002). Menard (2002) warned that for large coefficients, standard error is inflated, lowering the Wald statistic (chi-square) value. They recommended that the likelihood ratio test is more reliable and robust than Wald test and can be used to determine whether the covariates in the model are significantly associated with the outcome variable. Thus a preliminary indication of potentiality of the covariates can be obtained from the Wald statistics but reliable assessment of statistical significance can be done by likelihood ratio test. The likelihood ratio chi-square statistic is defined by the difference between deviance of reduced model and saturated model. The reduced model is formed by omitting a covariate from the saturated model. Under the null hypothesis that the coefficients are zero in multinomial logit model, change in deviance follows a chi-square distribution with 2 degrees of freedom. Mathematically,

$$\chi^2 = [L_R - L_F] \sim \chi_2^2 \qquad (12)$$

Here L_R and L_F are the -2 log-likelihoods for the reduced and final or saturated model respectively.

Table 1. Analysis of Maximum Likelihood Estimates of Potential Covariates

Logits	Covariates	Coeff ($\hat{\beta}$)	S.E ($\hat{\beta}$)	Wald Statistic	df	p-value	Odds Ratio exp ($\hat{\beta}$)	95% CI for exp ($\hat{\beta}$)	
								Lower	Upper
Logit 1: 1/3	Intercept	-2.64	0.14	346.60	1	.000			
	X_1	0.37	0.17	5.09	1	.024	1.45	1.05	2.00
	X_2	-0.32	0.16	3.87	1	.049	0.73	0.53	0.99
	X_3	0.54	0.16	11.23	1	.001	1.71	1.25	2.34
	X_4	1.65	0.18	83.78	1	.000	5.19	3.65	7.39
Logit 2: 2/3	Intercept	-2.04	0.11	340.75	1	.000			
	X_1	0.47	0.13	13.08	1	.000	1.60	1.24	2.06
	X_2	-0.55	0.13	17.33	1	.000	0.58	0.45	0.75
	X_3	0.43	0.13	11.50	1	.001	1.54	1.20	1.98
	X_4	1.84	0.15	160.65	1	.000	6.30	4.74	8.37

Table 2. Likelihood Ratio Test for Significance of Covariates

Model with Covariates	-2 log-likelihood	χ^2	df	*p*-value
Intercept only	417.448	266.910	8	<0.001
X_1	166.564	16.026	2	<0.001
X_2	170.201	19.663	2	<0.001
X_3	169.117	18.579	2	<0.001
X_4	340.441	189.903	2	<0.001
Final	150.538	-	-	-

The likelihood ratio (LR) chi-square test for the overall significance $(H_0 : \beta_1 = \beta_2 = \cdots = \beta_8 = 0)$ of all coefficients is presented in Table 2. The small p-value(< 0.001) from the LR test, would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero. The test suggests that as a whole the selected covariates have significant contribution to predict the outcome variable. The likelihood ratio chi-square statistic, degrees of freedom and corresponding p -value for individual covariate is also provided in Table 2 and indicates from the statistical point of view that all the covariates introduced in the model are significantly associated with the outcome variable.

In order to fit a model it is important to have tools to test for lack of fit. This is especially important for the multinomial logistic regression model, whose fit is notoriously difficult to visualize. Such tools are remarkably scarce in multinomial logistic regression applications (Goeman, 2006). Hosmer and Lemeshow (2000) suggested looking at the multinomial model as if it were a set of independent binary logistic regression models of each outcome against the reference outcome, and testing the goodness-of-fit of each of these separately. Instead of Hosmer-Lemeshow goodness-of-fit test, Deviance and Pearson's chi-square goodness-of-fit test can also be employed whether the model adequately fits the data (Hosmer and Lemeshow, 2000). In these tests, lack of fit is indicated by the significance value less than 0.05. To support the adequacy of the fitted model, a significance value greater than 0.05 is needed. The number of subpopulations with zero frequencies is small with $p > 0.05$, it may be concluded that the model fits the data well. The null and alternative hypothesis are stated as follows,

$$H_0 : E(Y) = \exp(X'\beta)/1 + \exp(X'\beta) \text{against } H_a : E(Y) \neq \exp(X'\beta)/1 + \exp(X'\beta)$$

The summary measures of goodness-of-fit tests are presented in Table 3.

Table 3. Summary Measures of Goodness-of-fit Tests

Name of the Test	Chi-square value	df	*p* -value
Pearson Chi-square	21.313	22	0.501
Deviance Chi-square	21.898	22	0.466
Hosmer-Lemeshow Chi-square for logit 1	3.264	5	0.659
Hosmer-Lemeshow Chi-square for logit 2	2.183	6	0.902

The high p-values corresponding to the Pearson and Deviance chi-square values implying the multinomial logistic regression model adequately fits the data. Hosmer-Lemeshow chi-square goodness-of-fit tests for both logits with high p-values reiterated that the model performance is excellent. Generally, Hosmer-Lemeshow chi-square test contains 8 degrees of freedom. But in the current study, both tests have degrees of freedom lower than 8. When Hosmer-Lemeshow chi-square goodness-of-fit statistic is calculated from fewer than 6 groups with large *p* -value, it will almost always indicate that the model fits the data well (Hosmer and Lemeshow, 2000).

The relationship between the logistic regression coefficient and the odds ratio provides the foundation for our interpretation of all logistic regression results exhibited in Table 1. Parameters with significant positive (negative) coefficients increase (decrease) the likelihood of that response category with respect to the reference category. For logit 1, the odds among the rural women having two living children are intended to desire for next child within two years is 1.45 times greater than the odds among the urban women. In other words, rural women having two living children are intended to desire for next child within two years is 1.45 times more likely than urban women. The confidence interval indicates that the odds could be as little as 1.05 times or as much as 2.00 times larger with 95 percent confidence. For logit 2, rural women having two living children are intended to desire for next child after two years is 1.60 times more likely than urban women and odds could be as little as 1.24 times or as much as 2.06 times larger with 95 percent confidence.

For logit 1, the professional women having two living children are intended to desire for next child within two years is 0.73 times less likely than the housewives and the odds could be as little as 0.53 times or as much as 0.99 times fewer with 95 percent confidence. For logit 2, professional women having two living children are intended to desire for next child after two years is 0.58 times less likely than the housewives and the odds of such desire for next child could be as little as 0.45 times of as much as 0.75 times fewer with 95 percent confidence.

For logit 1, the poor women having two living children are intended to desire for next child within two years is 1.71 times more likely than the middle class or rich women and the odds could be as little as 1.25 times or as much as 2.34 times larger with 95 percent confidence. For logit 2, the poor women having two living are 1.54 times more likely than the middle class or rich women to desire for next child after two years and the odds could be as little as 1.20 times or as much as 1.98 times larger with 95 percent confidence.

For logit 1, the women under study having sex preference are intended to desire for next child within two years is 5.19 times more likely than the women having no preferences about sex of the children and odds could be as little as 3.65 times or as much as 7.39 times larger with 95 percent confidence. Similarly for logit 2, the women having sex preference are intended to desire for next child after two years is 6.30 times more likely than the women having no preferences about sex of the children and odds could be as little as 4.74 times or as much as 8.37 times larger with 95 percent confidence.

4. Discussion and Conclusion

Global population rose to 6.9 billion in 2010, with nearly all of that growth in the world's developing countries. Overpopulation can result from an increase in births, a decline in mortality rates due to medical advances. More clearly, this accelerated population growth resulted from rapidly lowered death rates, combined with sustained high birth rates. The high growth rates are mainly driven by the high fertility rates. High fertility rates have historically been strongly associated with poverty, high childhood mortality rates, low status and educational levels of women, preferences of specific sex of children, deficiencies in reproductive health services, and inadequate availability and acceptance of contraceptives. Falling fertility rates and the demographic transition are generally associated with improved standards of living, increased life expectancy, lowered infant mortality, increased adult literacy, and higher rates of female education and employment (US, 2010).

Excessive growth must be checked to avoid this catastrophe. Many environmental, social, and economic problems either stem from or are increased in magnitude by the overpopulation. To ensure population stability not only in the increasingly wealthy third-world areas, but also in the industrialized areas, countries and individual must work together to achieve zero population growth. Zero population growth is the foremost American activist organization for population control. They cite several solutions for the population problem including family planning services, international awareness, population education, improving women's status, and economic incentives. Many of these solutions have been implemented in various countries with success. These are easy solutions with few adverse side effects (Ehrlich and Ehrlich, 1991).

The research exploring the impact of place of residence on desire for more children has been concerned with extent of exposure to urban and rural women. Findings from the study suggest that desire for children is significantly higher among the rural women than the urban women and hence revealed that higher fertility exists in rural areas than urban dwellers. The study was aimed to determine the influence of professional exposure to the desire for children and significant negative association was reported between occupational status and desire for children. The desire for children is significantly lower among the professional women than housewives.

Garenne and Joseph (2002) earlier found that poverty does not constitute an insuperable barrier to fertility decline. The current study suggests that poverty and high fertility are positively associated with demographic transition. The findings revealed that fertility is increasing among the poor women than middle class and rich women on the context of wealth index. Thus, it may be established that poverty is a key explanatory factor of high fertility and playing a role as a barrier to further fertility decline.

Das (1987) found no meaningful association between sex preference and desire for more children. But the current study established that child's sex preference has high impact on desire for next child and hence obstacle to further fertility decline. There is positive association between sex preference and desire for children and consequently increasing fertility trend in developing countries like Bangladesh is still directly influenced by the desire for sons or a particular sex composition of children.

The prior study (Sarkar and Midi, 2009) highlighted the importance of enhancing female education as part of a successful population policy. It was found that more educated women commonly tend to have desire smaller families specially women with post primary education markedly fewer children than women with no education. It is also established that women having post-primary education are using modern contraceptive methods significantly higher than the women having no-education.

Finally, it is strongly recommended that policymaker should pay attention to enhance women's standard of living by changing the existing policies and eliminate the discrepancies between rural and urban settings. Women status can be changed through inspiring them to involve in education and finally in the skilled-workforce and motivate to change their attitude toward family size. Advancement of female literacy and consequently their participation in the main stream of skilled-workforce can reduce poverty and eliminate the preferences of sex of the children and resume the fertility decline to achieve replacement level.

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