ECONOMIC GROWTH CENTER
YALE UNIVERSITY
P.O. Box 208269
New Haven, CT 06520-8269
http://www.econ.yale.edu/~egcenter/

CENTER DISCUSSION PAPER NO. 867

FERTILITY, CHILD WORK AND SCHOOLING CONSEQUENCES OF FAMILY PLANNING PROGRAMS: EVIDENCE FROM AN EXPERIMENT IN RURAL BANGLADESH

Nistha Sinha
Yale University

July 2003

I thank T. Paul Schultz for extensive discussions, valuable comments and suggestions. I am also thankful to Chris Udry and Bob Evenson for helpful comments. I am grateful to the Rockefeller Foundation for financial support and to the Economic Growth Center for providing excellent research facility.

Fertility, Child Work and Schooling Consequences of Family Planning Programs: Evidence from an Experiment in Rural Bangladesh

Nistha Sinha
Economic Growth Center
nistha.sinha@yale.edu

Abstract

Despite the attractiveness of experiments from the perspective of program evaluation, there have been very few program experiments in the area of family planning. This paper evaluates an ongoing family planning program experiment in rural Bangladesh. The paper estimates the effect of mothers' program exposure on fertility and children's time allocation. The results show that while the program was effective in reducing fertility, it had no significant impact on children's school enrollment. However, the program appears to have significantly raised boys' participation in the labor force.

Key Words: fertility, child labor, school enrollment, program evaluation

JEL classification codes: J13, J22, I21

1. Introduction

The question of whether family planning programs can reduce fertility and influence other household choices remains a concern for economists and other social scientists. Empirical evidence on the impact of the program appears to be mixed. For example, based on a careful analysis of the Indonesian fertility decline, Gertler and Molyneaux (1994) concluded that family planning program inputs did not play a major role in reducing fertility. Estimation of causal impact of the program on household behavior is complicated if program placement across regions is correlated with fertility in that region or if households migrate in response to program availability (Rosenzweig and Wolpin, 1986, 1988; Schultz, 1988). A potential alternative is to evaluate the effects of a randomized program or an experiment (Burtless, 1995). Despite the attractiveness of experiments from the perspective of program evaluation, there have been very few program experiments in the area of family planning mostly because they are costly to design and implement (Schultz, 1974). The Taichung City experiment is the most well known truly randomized experiment. It was conducted in 1963 as a pilot project for the Taiwanese national family planning program.[1]

This paper evaluates the impact of a carefully designed family planning program experiment in rural Bangladesh. In 1978, the International Centre for Diarrhoeal Disease Research, Bangladesh (ICDDR,B) introduced a family planning program experiment in Matlab thana (sub-district) where the ICDDR, B maintains a demographic surveillance system. In this experiment 70 out of 142 villages under demographic surveillance were provided an intensive family planning program maintained by the ICDDR,B. The key feature of this family planning program is that the village level variation in the placement of the program represents a random

[1] See Freedman and Takeshita (1969) for a description.

experiment (Phillips, Simmons, Koenig and Chakraborty, 1988).[2] The paper exploits this random nature of program placement to estimate the impact on fertility and on children's schooling and labor force participation. The impacts on children's schooling and work are unintended consequences of the program as households adjust to the changes in relative prices induced by the program.

When evaluating the cross-program impact of family planning programs, researchers have not focused on households' choice of sending children to work. In rural Bangladesh, fertility and children's work are expected to be closely related because children's economic contributions can be important for households (Cain, 1977; Cain and Mozumder, 1981). Empirical evidence from India shows that fertility tends to be higher in regions where child wages are high (Rosenzweig and Evenson, 1977). In a theoretical analysis of the consequences of a ban on child labor for household welfare, Basu and Van (1998) demonstrate that depending upon the conditions of the labor market and production technology, a high fertility-high child work or low fertility-low child work equilibrium could prevail in an economy. In the first equilibrium where households find it optimal to have high fertility family planning programs may not be successful in reducing fertility.

This paper uses data from the Matlab Health and Socioeconomic Survey (MHSS) which was fielded in 1996, 18 years after the program began (Rahman et al, 1999). The estimates show that the exposure to the program significantly reduced fertility. The program also resulted in a significant increase in boys' labor force participation but had a small and statistically

[2] Due to logistical and administrative considerations, program allocation across the villages was not random. However, the selection of villages was done such that program placement represented a random experiment.

insignificant impact on labor force participation by girls. The program did not have significant effects on school enrollments of boys or girls.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on program and cross-program impact of family planning programs. Section 3 describes the Matlab family planning program experiment. Section 4 describes the theoretical model. Section 5 describes the data and discusses the estimation strategy. Section 6 discusses the estimates of program impact on fertility. Section 7 discusses the estimates of program impact on children's labor force participation and their school enrollment. Section 8 concludes.

2. Evidence on Impact of Family Planning Programs

Family planning programs aim to reduce fertility by providing couples with modern methods of preventing unplanned (or unwanted) pregnancies. Studies that exploit geographical variation in program expenditure or in availability of family planning clinics to estimate program impact on fertility find that family planning programs are associated with lower fertility (Schultz, 1988; Rosenzweig and Wolpin, 1982; Hossain, 1989). However, estimates of program impact based on geographic variation in program intensity could be biased because (1) program placement might be correlated with unobserved community characteristics that also influence fertility (Rosenzweig and Wolpin, 1986) or (2) households might have migrated in response to program infrastructure (Rosenzweig and Wolpin, 1988).

Using regional or community level fixed effects estimation is one possible method to remove biases due to non-random program placement if the unobserved community characteristics that influence fertility are constant over time and program inputs vary. Fixed effects estimates show mixed evidence of the impact of program on fertility. Gertler and

Molyneaux (1994) use community level fixed effects to estimate the impact of a family planning program on contraceptive use, marriage probability and birth hazards in Indonesia. Their estimates suggest that the net impact of the family planning program on reducing fertility was very small. Pitt, Rosenzweig and Gibbons (1993) also find the fixed effects estimate of impact of family planning clinics on fertility to be statistically not significant in Indonesia. In contrast to the findings of Gertler and Molyneaux and Pitt, Rosenzweig and Gibbons, Duraisamy and Malathy (1991) find that using fixed effects increases the impact of program on fertility in their study of India.

The Taichung City (Taiwan) experiment conducted in 1963 is the earliest known family planning experiment. The design of the program was truly random where 2400 neighborhood units or lins in the city were randomly allocated into treatment and control groups. Couples where the wife was aged 20-39 were targeted (Freedman and Takeshita, 1969). The program resulted in increased acceptance of contraceptive methods particularly the intra uterine device (IUD).[3] Foster and Roy (1997) evaluated the Matlab family planning program using data from the 1974 and 1982 censuses of the ICDDR,B demographic surveillance area as well as data from the 1990 Knowledge Attitudes and Practices (KAP) survey. Their difference-in-differences estimate of the program impact shows that the family planning program significantly lowered the birth rates in treatment areas as compared to the control areas.[4] They also found that the impact of the program on birth rates increased with the length of program exposure. Four years after the

[3] A key finding of the experiment was that there were large information spillovers. Women who had not directly received program information learnt about the IUD through social networks. A number of women outside the city were found to have learnt about the IUD.

[4] The measure of fertility used in their analysis is the number of children aged 0-8.

program began in 1978, the birth rate in treatment area was 20% less than that in control area, and by 1990 the birth rate in treatment area was 25% below that in control area.[5]

The impact of family planning program might vary with characteristics of the program recipients, particularly schooling. Among other effects, schooling improves an individual's ability to process information, which in turn may raise non-market productivity (Rosenzweig and Schultz, 1989; Thomas, Strauss and Enrique, 1990). Family planning programs disseminate information about contraceptive technologies and thus might substitute for the improved information processing ability obtained through schooling (Schultz, 1988, 1992; Rosenzweig and Schultz, 1989). [6] Rosenzweig and Schultz (1982) found the interaction of female education and local level of family planning activity on fertility to be significantly positive for urban women aged 25 – 43 in Colombia implying that for this group of women the program acted as a substitute for schooling. However, the finding that programs substitute for female education does not appear to be universal. For example, estimates of impact of community health services on child health show that the program and mother's education are substitutes in some cases (Barrera, 1986 for Philippines; Thomas et al, 1990 for Brazil) and complements in others (Strauss, 1990 for Cote de Ivoire).

The effect of family planning programs on child schooling tends to be limited after controlling for availability of other programs and community infrastructure (Rosenzweig and Wolpin, 1982; Hossain, 1989). Fixed effects estimates of cross-price effects on schooling also

---

[5] Foster and Roy control for unobserved heterogeneity by including individual level fixed effects. They also control for the age and sex composition of other children in the household. Changes in these variables are potentially endogenous and the instruments for these include land ownership in 1974 and village characteristic variables.

[6] It can also be argued that the response of low education parents to availability of programs could be a reflection of the variation in price elasticities of demand across households with different levels of schooling (Schultz, 1997). High income households that also have more schooling tend to utilize services even in the absence of programs and their demand for services is less price elastic. Low income households who are more likely to have less schooling tend to be more price responsive (Gertler, Locay and Sanderson, 1987)

show statistically insignificant effects (Duraisamy and Malathy, 1991; Pitt, Rosenzweig and Gibbons, 1993). In contrast to these results, Foster and Roy's (1997) difference-in-differences estimates of the impact of the Matlab family planning program on schooling showed that the program significantly raised completed years of schooling only after the program had been in effect for 12 years. Controlling for the number, age and sex composition of siblings, Foster and Roy found that by 1990 the program had resulted in 30% increase in completed years of schooling of children aged 8-15 in program areas.

Researchers have sought to measure directly how households adjust their investments in child quality in response to a variation in fertility. Since child quantity and quality are both choice variables for the household and are determined by the same prices and household resource constraints, an exogenous source of variation in fertility is needed in order to estimate households' behavioral response to changes in fertility. In their test of the source of the empirically observed child quantity-quality tradeoff, Rosenzweig and Wolpin (1980) exploited the natural experiment of birth of twins, to estimate the impact of this exogenous variation in fertility on children's schooling attainment. Using data from rural households in India they found that the exogenous increase in number of children due to twin birth had a significant negative impact on the schooling of non-twin children in the household.[7] This estimate of the impact of fertility on child quality investments by parents, however, does not necessarily reflect how parents adjust investments in child quality when changes in prices or reproduction technologies induce variation in fertility. This is an issue that applies in general to studies that exploit natural

[7] Using a different approach, Rosenzweig and Schultz (1987) use data on contraceptive calendar to estimate reproduction technology and then estimate the impact of an unanticipated variation in fertility on children's schooling attainment and birthweight in Malaysia. Their results showed that fertility "shocks" or unplanned births significantly reduced schooling attainment and birthweight of children.

experiments (Rosenzweig and Wolpin, 2000). As will be shown below, the Matlab program induces a variation in contraceptive prices between program treatment and control villages that is uncorrelated with observables or unobservables that could influence fertility and human capital investment in children. Thus exposure to the Matlab program could be an instrument for fertility in a regression of schooling on fertility.

Very little is known about the impact of family planning program exposure on labor force participation by children. There is evidence showing that fertility tends to be higher in places where children's economic contributions to the household are high (Cain, 1977; Rosenzweig and Evenson, 1977; Cain and Mozumder, 1981). Rosenzweig and Evenson's (1977) seminal study of joint choices of fertility, children's schooling and labor force participation from rural India estimated the cross-price effects of child wages. They found that at the district level, child wages had a significantly positive impact on fertility (measured as number of children aged 5-9 per woman aged 15-44) after controlling for adult wages, land holdings and schooling of adult men and women. The positive effect of child wages on fertility implies that total non-work time per child (school plus home time) and fertility are compensated substitutes.

3. Matlab Family Planning Program

This paper evaluates the impact of the family planning program experiment implemented by the ICDDR,B in Matlab sub-district in rural Bangladesh. The region is a low-income, predominantly agricultural economy located southeast of Dhaka. The region experiences yearly floods between June and October when all land other than homestead land and orchards are submerged. The ICDDR,B has maintained a demographic surveillance system in Matlab since

1966 (Aziz and Mosley, 1994).[8] In 1978, the ICDDR,B introduced the family planning program in 70 of the 149 villages covered by the demographic surveillance system. By 1987 the total number of villages under demographic surveillance was 142 since 7 villages in control area disappeared due to river erosion (ICDDR,B, 2001). The Matlab family planning program experiment was designed to test whether the provision of low cost contraceptives services could induce demographic change in a society in the absence of economic development (Phillips et al, 1982).

The village level variation in the placement of the program is considered to represent a random experiment (Phillips, Simmons, Koenig and Chakraborty, 1988).[9] The treatment and control villages have similar economic conditions and at the start of the program had similar demographic conditions as well. All currently married women residing in treatment villages receive the program treatment (Phillips, 1994). There is some diffusion of program information into control villages because of migration between the villages due to marriages (Phillips et al, 1988).

[8] The demographic surveillance consists of periodic censuses, socioeconomic surveys and a continuous registration of all vital events, marital union-dissolution, household division and headship change in the study population. The work of ICDDR,B in Matlab has a much wider scope than family planning. A recent New York Times article briefly described the contributions made to public health and social sciences through the research carried out in Matlab (Waldman, 2003).

[9] The experiment was designed to test the high quality ICDDR,B program against the government program and the treatment and control villages were supposed to be similar with regards to the level of government program effort. However, as the Matlab program proceeded, the government effort in the treatment villages was significantly reduced (Koenig, Rob, Khan, Chakraborty and Fauveau, 1992). What this implies is that this aspect of the experimental design has been compromised in the actual implementation of the program. Thus, the treatment-control differences in demographic outcomes cannot be attributed to the incremental program effort of the ICDDR,B.

3.1 The Intervention

Under the program, the 70 villages with the program receive family planning services from the ICDDR,B while the control villages receive only the government family planning services. Thus, there is variation in the intensity and quality of family planning services available across treatment and control villages.

The ICDDR,B family planning program is characterized by the outreach program consisting of home visits by trained female outreach workers. There are 80 female outreach workers in the treatment area and they visit all households in their village once every two weeks (Aziz and Mosley, 1994). During home visits, outreach workers provide information to women about contraceptives and management of associated side-effects and motivate them to continue use. They also provide non clinical methods (pills, condoms, foam tablets) and administer depo-medroxyprogesterone acetate (DMPA) injections. Regular home visits by outreach workers is key to the success of the program in this rural setting where cultural norms restrict women's physical mobility. The doorstep delivery of information and contraceptives effectively reduces the price of contraceptives for the households. The outreach workers are supported by female paramedical and medical workers who are available in 4 clinics serving the treatment area villages.

3.2 Other Programs in the Area:

Two programs available in the Matlab area are of relevance to the present study. First, maternal and child health (MCH) program is available in treatment and control villages. In the case of this program too there are variations between the ICDDR,B run program in treatment villages and the government run program in the control villages. The delivery of MCH services is integrated with the delivery of family planning services in both ICDDR,B and government program. Thus, part of the difference in outcomes between the two areas can be attributed to differences in MCH program as well. The MCH and family planning programs are complementary in their objectives and the presence of both types of programs should enhance each program's impact on the program objective.

Second, school reforms and programs were introduced countrywide starting in 1990 (Khandker and Samad, 1995; Alam, 2000). These programs included reform of government primary schools, food for education program and a secondary school scholarship program for girls. There is no direct data on the specific reforms or types of school programs in Matlab. However, since the program area covers a small geographic area there is likely to be little variation in these programs across treatment and control villages.

The program had a large initial impact on fertility. The program began in 1978 and by 1979, general fertility rate in treatment area villages was 25% lower than that in control villages (Phillips et al, 1982).[10] Foster and Roy (1997) found that the impact of the program on birth rates increased with length of exposure to the program.

4. Model of Household's Response to Family Planning Program

The household demand framework can be used to understand how program exposure can influence household behavior. Exposure to the family planning program is modeled as a reduction in the price of children since it lowers the fixed cost of raising children, a cost that is independent of the level of per child quality (Becker, 1991; Rosenzweig and Wolpin, 1982). In

[10] General fertility rate was measured as the total number of births in a time period divided by the estimated number of women aged 15-44 in the area (Phillips et al, 1982).

what follows, the framework of Rosenzweig and Wolpin (1982) is adapted to obtain the predicted effects of change in fixed price of children on fertility and on children's schooling and labor supply.

Parents have preferences over number of children (N), each child's school attendance (S) and leisure (L) and current consumption of other goods (Z). The utility function below characterizes these preferences.

$$U = U(N, S, L, Z) \quad (1)$$

In order to highlight the impact of change in price of children on the variables of interest, the model suppresses parent's labor-leisure choice. This implies that household income (Y) other than children's contribution is exogenously determined in the model. [11]

Children in rural Bangladesh engage in economically productive activities from a young age (Cain, 1977; Cain and Mozumder, 1981). The model reflects this by allowing parents to choose the allocation of child's time between school (S), work (H) and leisure (L). The model also makes the simplifying assumption that labor markets are perfectly competitive. This implies that any household member seeking work can find one at the going wage rate. Competitive labor markets can be considered to be a close approximation to the structure of rural labor markets in Bangladesh (Cain and Mozumder, 1981). [12]

Equations 2 and 3 below show the household's budget constraint and each child's time constraint.

$$p_n N + p_S SN + p_z Z + p_c (N_{max} - N) = Y + wHN \quad (2)$$

[11] Household production functions are also suppressed in this model.

[12] The Matlab program could potentially influence the level of child wages in the study by reducing the supply of child workers in the program areas. Capturing these dynamics of the program impact is beyond the scope of the present paper.

$$S + H + L = \Omega \quad (3)$$

The price of children that is independent of child quality is given by p_n and p_c is the price of averting births through contraception. N_{max} is the maximum number of births a couple could have if they do not regulate their fertility (natural fertility). The price of school attendance for each child is p_s which may represent tuition fee and price of textbooks. The price of other goods consumed by the household is given by p_Z. The total economic contribution by children's work is wHN where w is the child wage rate, and H represents hours worked by each child.

In this model each additional birth demanded by the household lowers the expenditure on fertility regulation ($p_c \times (N_{max} - N)$). Therefore the fixed price of an additional child is determined not just by p_n which reflects all the costs of raising children that are independent of chosen quality of each child but also by p_c. The fixed price of an additional child net of the price of contraceptives is ($p_n - p_c$) (Rosenzweig and Wolpin, 1982). The variation in the intensity and quality of family planning program intervention between treatment and control area produces a variation in p_c across villages and hence a variation in the net price of births (p_n - p_c). One of the key features of the Matlab family planning program experiment is the outreach program where during home visits, trained female outreach workers deliver contraceptives and information. For women, the time costs of obtaining contraceptives from sources such as shops and clinics may be high in rural Bangladesh particularly due to cultural norms that restrict women's physical mobility. The reliable and high quality doorstep delivery of services by outreach workers in the treatment villages effectively reduces the costs of obtaining and using contraceptives. Thus, treatment area p_c is lower than control area p_c. Corresponding to this variation in p_c, the fixed price of an additional birth net of contraceptive prices is higher in treatment villages as compared to the control villages.

Let p^*_n represent the fixed price net of contraceptive prices, then the household's full income constraint is given by equation 4 below.

$$F = Y + wTN - p_c N_{\max} = p*_n N + (p_S + w)SN + p_z Z + wLN \qquad (4)$$

Parent's utility is maximized subject to the full income constraint.[13] This maximization yields reduced form demands of the form:

$$\text{I} = f(p*_n, p_s, p_z, w, Y, N_{\max}),\ \text{I = N, S, L, Z} \qquad (5)$$

From the reduced form equation it can be seen that by influencing the fixed price of children, the Matlab program affects not just demand for children but all household choices. The effect of changes in the fixed price of children on demand for children, their schooling, leisure and work can be derived from the model. In order to derive the effects of price change predicted by the model, Slutsky equations are used to decompose the price effects of a change in p^*_n (holding constant all other prices and exogenous income) into a compensated substitution effect (price effect) and an income effect.

$$\frac{\partial I}{\partial p_n^*} = \frac{\partial I^U}{\partial p_n^*} - N\frac{\partial I}{\partial F}, \quad \text{I = N, S, L} \qquad (6)$$

The superscript U indicates utility-compensated demands.

Using equation 6, the sign of the impact of a change in p^*_n on demand for children or fertility, the own price effect, can be derived. The own compensated substitution effect is negative implying that a rise in the fixed price of children will reduce fertility. The sign of the income effect for fertility is not prescribed by theory, however empirical evidence suggests that

[13] From the first order conditions of constrained utility maximization, the shadow price of child quantity is $p_N = p_n^* + p_s S - wH$, the shadow price of schooling is $p_S = (p_S + w)N$ and the shadow price of child leisure is $p_L = wN$. Changes in fixed price of children directly affect the shadow price of children and by affecting the choice of N, they indirectly affect schooling and labor supply as well. Child earnings reduce the shadow price of child quantity (given S) and raise shadow price of schooling and leisure.

this income effect is positive (Schultz, 1997). The Slutsky equation then implies that the uncompensated own price effect will be negative. Thus, treatment under the Matlab program is expected to reduce fertility.

Equation 6 also shows that the rise in fixed price of children due to program treatment produces substitution and income responses in children's time allocation between leisure, school and work. The sign of the observed uncompensated cross-price effects for schooling, child leisure and labor supply are not predicted by theory. Empirical evidence shows that the compensated cross substitution effect between child quality (measured by schooling) and fertility is positive implying that parents view fertility as a substitute for child quality (Rosenzweig and Wolpin, 1980; Rosenzweig and Schultz, 1987). From the Slutsky equation, a positive cross substitution effect and a positive income effect together can produce uncompensated cross price effects which are small or possibly negative (if income effect is large compared to the substitution effect).

The Slutsky equation for each child's labor supply can be obtained by exploiting the time constraint given by equation 3. [14]

$$\frac{\partial H}{\partial p_n^*} = -\left[\frac{\partial (S^U + L^U)}{\partial p_n^*} - N\frac{\partial (S^U + L^U)}{\partial F}\right] = \frac{\partial H^U}{\partial p_n^*} - N\frac{\partial H}{\partial F} \tag{7}$$

As can be seen from equation 7, the compensated cross substitution effect for labor supply is determined by the compensated cross substitution effects for schooling and child leisure. Empirical evidence shows that fertility and child wage are positively related or $\frac{\partial N}{\partial w} > 0$

---

[14] $\frac{\partial H}{\partial p_n^*} = \frac{\partial (T - (S + L))}{\partial p_n^*} = -\left[\frac{\partial (S + L)}{\partial p_n^*}\right]$ and $\frac{\partial H}{\partial F} = \frac{\partial (T - (S + L))}{\partial F} = -\left[\frac{\partial (S + L)}{\partial F}\right]$.

(Rosenzweig and Evenson, 1977). This implies that that number of children and (S + L) or the total hours spent by each child in non-work activities are compensated substitutes (given that that children are normal goods for the household). Exploiting the symmetry of compensated cross-substitution effects, the sign of $\frac{\partial(S^U + L^U)}{\partial p_n^*}$ is expected to be positive as well. This implies that hours of child's labor supply and p^*_n should be negatively related. Since schooling and child leisure are non-inferior goods for the household, the income effect for child's labor supply will consequently be negative.[15] The uncompensated cross-price effect of a change in p^*_n on H will therefore depend upon the relative magnitudes of the negative substitution effect and the negative income effect.

The household demand framework predicts that exposure to the Matlab program will result in lower fertility but the effects on schooling and child's labor supply are ambiguous. In the case of the cross-price effects, the Slutsky decomposition shows that the income effects contained in the observed uncompensated effect of program exposure work to weaken the compensated cross-substitution effects. The income effects associated with the price change induced by the program can be expected to be large since the study area is a low-income rural economy. [16]

In the empirical application below the reduced form demand relations given by equation 4 are estimated. Fertility is measured as the number of children ever born. Current enrollment in

[15] This negative income effect for children's labor supply implies that labor supply by children decreases with increases in household income. Data from across the developing world shows that children who work tend to belong to low income households. A testable implication of the Basu and Van (1998) model is that children participate in the labor force if household income falls below a certain benchmark (subsistence) level. Ray (2000) tests this hypothesis using data from Pakistan and Peru and finds a significant effect of being below the poverty line on children's hours of labor supply in Pakistan.

[16] Studies evaluating the Matlab program frequently note that the study area continues to be characterized by low economic growth. See for example, Phillips, Simmons, Koenig and Chakraborty (1988).

school (S>0) and participation in economically productive activities (labor force participation) (H>0) are used due to the lack of data on hours spent in school and hours spent in work. The next section discusses the data and describes the variables used in the analysis.

5. Data Description and Estimation Strategy

This paper estimates the impact of the Matlab program using data from the 1996 Matlab Health and Socioeconomic Survey (MHSS) which surveyed 4,364 households residing in 141 villages in the surveillance area covering both treatment and control villages (Rahman et al, 1999). The primary sampling unit was the bari or the residential compound (containing a cluster of households) since this is the basic unit of social organization and is thought to be the relevant decision-making unit in rural Bangladesh. Baris were randomly selected using the 1994 demographic surveillance sample frame. In each selected bari a maximum of two households were selected for interview. The survey collected detailed economic and demographic data at the individual, household and village levels. In order to assess the program impact on fertility, child work and enrollment, a sample of ever married women and a sample of children aged 10 –16 were created.

There are 4,892 women in the ever married women sample and 2,520 children in the children sample.[17] Both samples contain household and village characteristics data. The data cover 139 villages with 70 villages in the treatment area and 69 in the control area.[18] The ever

[17] The sample of ever married women consists of women aged 15 and older residing in the household who were also selected for the ever married women survey and for whom there are no missing observations. Of these women 84% are currently married, 14% are widows and the remaining are divorced or separated. The children sample consists of children whose mothers were selected for the ever married women survey and who were residing in the household at the time of survey and were selected for further interviews. Girls make up 48% of the children sample.

[18] The MHSS covered 141 villages of which community survey was completed in 140 villages. A merging of household and village level data shows that there are 2 villages with incomplete community survey. Thus, there is complete data on only 139 villages.

married women sample contains women aged 15 to 91. This age range includes women who had most likely completed their fertility before the program was introduced in 1978. [19] The variation in the fertility of women aged 58 and older across treatment and control areas provides us with an estimate of pre-program differences in fertility. For each woman in the ever married women sample, there are data on children ever born, pregnancy history and contraceptive use as well schooling history.

For children, there are data on schooling history and current enrollment. Information on whether a child was participating in the labor force at the time of survey was put together using responses to two questions asked in the survey. In the household roster, the head was asked the occupation of each individual in the household aged 10 years or older. One of the options in response to this question was that the child was a student. Thus, responses to this question yielded current labor force status of those children who were most likely not enrolled in school or were spending a relatively higher number of hours on the non-school activity. In order to measure labor force participation by children enrolled in school at the time of survey, the schooling histories were used instead which asked whether the respondent was engaged in productive activity while enrolled in school. Responses to the occupation question and the schooling histories were combined to obtain data on each child's current labor force participation status. This measure of child's labor force participation would be independent of his or her enrollment status. [20]

The household head's report of children's occupation provides some information on the type of work that children are involved in. Boys are mostly involved in agriculture, working on

[19] The distribution of women by age cohort is as follows: (1) 58 and older: 14% (2) 50 – 57: 14% (3) 15 – 49: 71%.
[20] Cross tabulations indicate that about 28.5% of girls and 30% of boys were enrolled in school and working at the time of survey.

land owned by the household or working as agricultural laborers. They also work as fishermen and shopkeepers. Girls are mostly involved in raising poultry and in activities such husking, boiling or drying paddy.

Two determinants of fertility, child work and schooling are not explicitly included in the analysis. These are price of schooling, p_s, and child wage, w. There is likely to be little variation across villages in the price of schooling which includes price of school uniforms and textbooks. In its community survey, the MHSS surveyed schools serving the Matlab area. A tabulation of the data on primary schools shows that children do not pay tuition though some schools charge admission fees. Children also do not pay for textbooks since the government provides them free of charge. [21] A community survey collected data on child wage rates in agriculture, industry and cottage industry. The data tend to be missing for most of the villages surveyed and their use would have resulted in loss of observations. Cain's work shows that non-farm wage work by both adults and children is important in rural Bangladesh (Cain, 1977; Cain and Mozumder, 1981). Distance of the village from the thana headquarters, which is the only urban area in this sub-district, is used as a proxy for opportunity for (non-farm) market work.

5.1 Survey Design

In the MHSS, within-bari selection of households and within-household selection of individuals produces a sample that is not representative of households and individuals in Matlab DSS area (Rahman et al, 1999). Sample means therefore have to be weighted using the inverse of sampling probability in order to obtain an unbiased estimate of population means (Deaton,

[21] A tabulation of the data on primary schools shows that in the 80 schools surveyed, boys and girls do not pay tuition though some schools charge admission fees, all applicants are admitted into school, boys and girls do not pay for textbooks and government is the main provider of text books.

1997). Furthermore, if respondents' selection into the sample is closely correlated with any dependent variables (fertility, children's schooling or labor force participation) then regression estimates that do not account for the survey design will yield biased estimates (Wooldridge, 2002). In such cases, weighted estimators that account for the probability of selection produce consistent estimates of the population parameters.[22]

In the MHSS, up to 2 households were picked per bari. One household per bari was chosen at random while the second household in multiple household baris was selected if it contained elderly relatives so as to oversample elderly respondents (aged 50+). Within the household, respondents had varying probability of being selected into the survey depending upon the age of the respondent, marital status and relationship to the household head. Probability of selection of respondents within the household varied according to age as follows: (1) household members aged 50 and over were always selected (2) Of the 0-14 year olds in the household, two children were selected (3) those in the 15-49 age group had varying probabilities of selection.[23]

Weights equal to the inverse of probability of selection are applied to produce summary statistics for the ever married women sample and the children sample.[24] Since respondents' selection into the survey is not correlated with their fertility, no adjustments for the survey design

---

[22] It is important to note here that weighting for unequal sampling probability does not imply that the errors in the regressions are heteroscedastic of the form $\sigma^2 W_i^{-1}$ where W_i is the ith respondent's sampling weight. Instead, the sampling probability represents a sample selection rule that results in heteroscedasticity in the error term that is a function of the censoring of the dependent variable due to the selection rule (similar to that arising in selection models). Stata calculates a consistent estimator of the variance-covariance matrix that incorporates sampling weights (StataCorp., 1999). In the case of linear regression, this design based variance – covariance estimator reduces to White's heteroscedasticity consistent estimator if the sample were a simple random sample. Also see Wooldridge (2002) for a discussion.

[23] This depended upon whether they were i) spouses of an elderly (50+) member of the household, ii) the household head, iii) spouse of the household head, iv) not in any of these categories (never married individuals).

[24] Weight = Household weight * Within household selection weight of respondent
=(1/Pr(household selection in bari))*(1/Pr(selection of respondent))
The weights applied in the summary statistics and regression estimates were adjusted for very large weights by capping the weights of those in the top 1% of the distribution.

(other than for clustering of observations) need be made in the fertility regressions.[25] In the children's sample, the survey design implies that probability of selection is an inverse function of mother's fertility since two children aged 0-14 were picked from each household. Thus, estimates of the schooling and labor force participation equations have to be adjusted for the survey design. This is not because children from higher fertility households are underrepresented but because mother's fertility and children's schooling and labor supply are choices made by the household. The children sample is therefore a choice based sample and ignoring survey design would produce biased estimates. Accordingly, weights equal to the inverse of probability of selection were applied to produce estimates of schooling and labor force participation equations that are reported below.

5.2 A Check of Random Program Placement

Table 1 presents weighted means and difference in means between treatment and control area for women who were 40 or older in 1978, the year the Matlab experiment started. These women would be aged 58 or older at the time of survey in 1996. The oversampling of the elderly in the MHSS enables a comparison of characteristics of women belonging to treatment and control villages. There are 768 women in the ever married women sample who belong to this cohort. Women belonging to this cohort had the least exposure to the program and can be considered as the pre-program cohort. A comparison of fertility and other characteristics of this cohort by treatment and control village residence at the time of survey provides some evidence

[25] In such cases, unweighted estimators are more efficient than weighted estimators are. See Wooldridge (2002) and references therein.

of systematic differences between these villages prior to program initiation and hence provides a check for random program placement.

The pre-program difference in mean fertility of treatment and control area women is 0.18, which is statistically not significantly different from zero at the 5% level. This indicates that pre-program treatment and control area women had similar fertility. As seen in Table 1, treatment and control women in the pre-program cohort do not significantly differ in mean levels of own education, husband's education and distance of their village from district headquarters. Ownership of farmland shows that significantly fewer pre-program women in treatment villages reside in households with large (1.625 acres or more) farmland. However, due to household partition, land ownership at the time of survey is unlikely to correctly reflect ownership at the time the program began. In Matlab thana 90% of the population is Muslim while among the remaining population the majority are Hindus. Table 1 shows that among pre-program women there is a significantly higher percentage of Hindu households in treatment villages as compared to control villages. This characteristic of program placement is thought not to have significant effect on program impact (Phillips et al, 1988). Overall, the differences in means for the pre-program cohort of women presented in Table 1 suggest that program placement can be considered to be random. [26] Thus, post program differences in fertility can be attributed to the program.

[26] Using data from 1974, Chowdhury and Phillips (1984) report that there were no significant pre-program differences in social and economic characteristics of married women living in treatment and control villages.

5.3 Descriptive Statistics and Difference Estimates of Program Impact

In what follows, impact of program on fertility, children's school enrollment and labor force participation is estimated for women who were potentially exposed to the Matlab program for most or all of their reproductive life. Differences in means between treatment and control area women and children provide an estimate of program impact since a check of the data indicated that program placement can be considered to be random. Consider the mean of the outcome of interest, Y (fertility). Let a_0 be a control area specific effect and a_1 be a treatment area specific effect. Also let b_0 and b_1 be time specific effects such that b_0 refers to the period before the program was introduced and b_1 refers to the period after the program was introduced. Then the mean pre-program outcome in control villages is $Y_{00} = a_0 + b_0$ and the mean post program outcome in control villages is $Y_{01} = a_0 + b_1$. The mean pre-program outcome in treatment villages is given by $Y_{10} = a_1 + b_0$. The mean post program outcome in treatment villages is $Y_{11} = a_1 + b_1 + d$, where d represents the impact of the program intervention. Then the difference estimator is $(Y_{11} - Y_{01}) = (a_1 - a_0) + d$. The difference estimator is an unbiased estimator of d only if $a_1=a_0$. The comparison of means for the pre-program cohort of women suggested that $a_1=a_0$ since the difference in mean fertility was not significant (Table 1).

Women who were 57 or younger at the time of survey can be considered to be post program women since this cohort of women would have been 39 or younger in 1978. The cross-program effects on children's schooling and labor force participation are estimated for 10-16 year olds who are children of these post program cohort of women. Thus, the analysis of the

---

Phillips et al (1982) compared the pre-program and post-program age specific fertility rates in treatment and control villages. They found no significant pre-program differences in age specific fertility rates.

paper is based on 4,124 women in the ever married women sample belonging to the post program cohort and 2,500 children in the children sample.

Table 2 presents weighted means and standard deviations of variables for the post program ever married women sample. The mean fertility of this group of women is 4.29. More than half the women in the sample reside in treatment villages. About 13% of the women are Hindus. On the average women have 2.21 years of education while their husbands have 3.33 years of education. The pattern of size of farmland owned indicates that most women in the sample belong to land poor households and a small percentage belong to households that own medium sized (26%) and large sized (12%) farms.

Table 3 compares weighted means and difference in means by program exposure for the post program cohort of women. The difference in mean fertility between treatment and control area women is –0.39, which is statistically significant at the 1% level. This represents approximately a 9% reduction in fertility due to program treatment evaluated at the weighted sample mean fertility (-0.39×4.29).

Table 4 presents descriptive statistics using the children sample that are weighted for unequal sampling probabilities. The sample is restricted to children whose mothers belong to the post program cohort (aged 57 or less in 1996) in order to obtain a sample of children whose mothers had maximum exposure to the program. This resulted in a sample of 2,500 children. As seen in Table 4, 33% of girls are working as compared to 39% of boys. This difference may in part be due to the fact that the way labor force participation is measured in this paper it does not pick up non-market work (such as care of older siblings) that girls tend to be involved in more than boys. A large percentage of boys and girls, 80% and 86% respectively, were enrolled in school at the time of survey.

Table 5 compares weighted means and difference in means by sex and program exposure. As seen in Table 5, 43% of the boys in treatment area were participating in the labor force as compared to 35% of boys in control areas. This difference is statistically significant at the 5% level implying that for boys program treatment is associated with 8% increase in labor force participation rates. For girls, the labor force participation rates do not differ significantly. About 33% of the girls in treatment area and 32% of the girls in control area participate in the labor force and this difference in girls' participation rates is statistically not significant. The difference in boys' enrollment rate between treatment and control area is also not significant. Similarly, the treatment-control difference in girls' enrollment rate is also not significant. Girls' enrollment is higher than boys' enrollment in both treatment and control area indicating that factors other than the family planning program might be influential.[27] The relatively higher percentage of Hindus in treatment villages is reflected in the children sample as well.

The random nature of program placement suggests that an appropriate estimation strategy for obtaining mean program impact is to calculate post program differences in outcomes between treatment and control area. This estimation strategy can be exploited in a regression framework since random program placement across villages ensures that variation in program exposure across households is not correlated with unobserved variables. The regression framework also permits inclusion of additional variables that control for observable differences in characteristics that might influence fertility, children's schooling and labor supply. This reduces any possible bias arising from observable differences between the treatment and control groups. The inclusion

[27] Foster and Roy (1997) note the positive trend in girls' schooling relative to boys' schooling in both treatment and control areas between 1974 and 1990. They attribute this to increase in employment opportunities for women and change in returns to schooling in the marriage market.

of additional covariates also improves the precision of the estimates of the effect of treatment on the treated.

6. Effect of Program on Fertility

This section describes how program impact on women's cumulative fertility is estimated in a regression framework. Equation 8 shows the reduced form fertility equation based on equation 4. The fertility equation is estimated data on women belonging to the post program cohort (57 or younger).

$$N_{ihjk} = a + b_1 T_k + b_2 E_{ihjk} + b_3 T_k \times E_{ihjk} + b_4 T_k \times R_{ihjk} + X_{ihjk} d + e_{ihjk} \qquad (8)$$

N_{ihjk} represents lifetime fertility of woman i residing in household h in bari j and village k. The measure of fertility used here is the number of children ever born. T_k is a village level dummy variable that takes value 1 if woman is in a treatment village and 0 otherwise. This dummy variable measures variation in program exposure. In terms of the model presented in section 2, T_k =1 represents an decrease in price of contraceptives relative to T_k=0. E is woman's education and R is a dummy variable representing her religion that takes value 1 if she is Hindu and 0 if she is Muslim. Equation 8 includes interaction terms between program exposure and woman's education and program exposure and religion to estimate the distribution of program impact. X contains household and village characteristics namely, husband's education, size of farmland owned and distance of village from Matlab thana headquarters. The error term ε_{ihjk} is assumed to be independent across baris and clustered for observations within the bari.

Estimates of Fertility Equation

Table 6 presents results based on equation 8 for women aged 15-57 at the time of survey. It reports marginal effects based on maximum likelihood estimates of the Tobit model. It also reports least squares estimates for comparison. Both sets of estimates correct for clustering of the error terms. Columns 1 and 4 report results with only age and square of age as additional controls aside from program exposure. Columns 2 and 5 include the remaining control variables. Columns 3 and 6 include interaction terms between program exposure and female education and program exposure and religion.

Least squares and Tobit model marginal effects estimates are similar in sign and in statistical significance since only about 6% of the women in this sample had zero births. As seen in columns 1 and 4, program exposure is associated with a significant reduction in fertility. When controls for woman's age are introduced to control for incomplete fertility, the difference estimator increases in absolute value from 0.39 (Table 3) to 0.61 (Tobit marginal effect estimates, column 4). Introduction of additional controls for woman's education, husband's education, religion, ownership of farmland and distance to thana headquarters reduces the magnitude of the treatment residence coefficient somewhat (Columns 2 and 5). Based on this specification (Column 5), the Tobit marginal effect estimate of program impact of –0.553 evaluated at the weighted sample mean fertility translates into a 13% (-0.553/4.29) reduction in fertility.

Foster and Roy (1997) estimated that the program had reduced birth rates (number of children aged 0-8) in the treatment area by 25% by 1990 (12 years after program had been in place). This implies that the program had a significant impact on birth spacing. The estimate of 13% decline in lifetime fertility obtained here is smaller than the impact on birth rates estimated by Foster and Roy. This is consistent with women in program area using the available modern contraceptive methods (mostly DMPA injections) to space children and to postpone births to older ages (Schultz, 1974).

Husband's education and distance to thana headquarters do not appear to have significant impact on fertility. Ownership of farmland is associated with a significant increase in fertility. Female education and being Hindu are associated with significant reduction in fertility. For example, based on Tobit marginal effect reported in Column 5, for Hindu women who received the program treatment, the average program impact is –0.916 (-0.553 + (-0.363)) which translates into a 21% reduction in fertility. This suggests that program impact might vary with characteristics of the woman.

The specifications in Columns 3 and 6 further explore this heterogeneity in program impact by allowing the impact of program treatment to vary by wife's education and by religion. The Matlab program-education interaction estimate is positive which indicates that the program is acting as a substitute for female education. The Tobit marginal effect estimate of the interaction term is statistically not significant while the least squares estimate is significant at the 10% level. The program-religion interaction (Hindu × Treatment) estimate is statistically not significant at the 5% or 10% level but the estimate is negative suggesting that the program has widened the gap in fertility of Hindu and Muslim households.

7. Effect of Program on Boys' and Girls' Labor Force Participation and Enrollment

The impact of mothers' program exposure on children's labor force participation and school enrollment are also estimated in a regression framework. These cross-program impacts are estimated in two ways. First, a reduced form relationship between program exposure and labor force participation and program exposure and enrollment (based on equation 4) are estimated for boys and girls separately. Equations 9 and 10 show the reduced form regression equations.

$$Y^1_{ihjk} = a^1 + b^1_1 T_k + X_{ihjk} d^1 + e^1_{ihjk} \quad (9)$$

$$Y^2_{ihjk} = a^2 + b^2_1 T_k + X_{ihjk} d^2 + e^2_{ihjk} \quad (10)$$

Y^1_{ihjk} represents the probability of participating in the labor force for child i residing in household h and bari j in village k. Y^2_{ijk} represents the probability of being enrolled in school for child i residing in household h in bari j and in village k. T_k is a village level dummy variable that takes value 1 if a child resides in a treatment village and zero otherwise. X contains household and village characteristics namely religion, mother's and father's education, size of farmland owned and distance of village from Matlab thana headquarters. The error terms ε^1_{ihjk} and ε^2_{ihjk} are assumed to be independent across baris and clustered for observations within the bari.

In the second approach, labor force participation and current enrollment regressions are conditioned on mother's fertility. Fertility is potentially endogenous in these regressions since unobserved variables that influence children's labor force participation or schooling will also influence mother's fertility. Program exposure measured by residence in a treatment area village is available as a suitable instrument for fertility since program placement is random and hence not correlated with unobserved variables or observed variables that influence children's labor force participation or schooling. Thus, randomized nature of the program is exploited to obtain

Two Stage Conditional Maximum Likelihood (2SCML) estimates of the impact of fertility on children's labor force participation and school enrollment (Rivers and Voung, 1988). [28]

7.1 Reduced Form Estimates of Child Labor Force Participation and Enrollment

Reduced form estimates of children's labor force participation equation and current enrollment equation are reported in Table 7. Marginal effects from probit model maximum likelihood estimation of equations 9 and 10 are reported. The estimation adjusts for clustering of the error terms and weights are applied to adjust for unequal sampling probability.

Columns 1 and 2 in Table 7 report results for boys' labor force participation. Columns 3 and 4 report the estimates of labor force participation equation for girls. Columns 1 and 3 do not include household and village characteristics as controls. Columns 2 and 4 include dummies for religion, parents' education, farmland owned by household as well as controls for mother's age and the distance of the village from thana headquarters. Results show that controlling for these variables increases the effect of the program. The intensive program is associated with 11% increase in labor force participation by boys. The program appears to have had a very small positive impact on labor force participation by girls but this impact is statistically not different from zero.

Estimates of program impact on boys' and girls' labor force participation are both positive but significant only in the case of boys' labor force participation. These estimates do not imply that parents view child work and fertility as substitutes since these are uncompensated

[28] Of the 1,841 households represented in the children sample, 1,242 have only one child in the sample, 539 have 2 children and 60 have 3 children in the sample. In the case of households that contribute 2 or 3 children to the sample, mother's fertility in the 2SCML estimates is counted as many times. In the 2SCML estimates, the first stage equation for mother's fertility is estimated separately for boys and for girls.

program effects and include both the substitution and income effects. From the discussion in section 4, positive uncompensated effect on child's labor supply could arise even if the compensated substitution effect was negative, if the income effect was relatively large. The estimates of program impact on labor supply obtained here suggest that income effects might have played an important role. As noted earlier, the income effect can be expected to be large given that Matlab is a relatively poor rural area.

Variables that proxy for household income have large impacts on boys' and girls' labor force participation. Ownership of farmland controls for household income but it might also be correlated with children's productivity and hence might be associated with an increase in demand for child work. For example, Cain (1977) shows that children from landless households worked only after the age of twelve, when they became employable as wage laborers, but those from households with farmland began working on household plots from younger age. The estimates in columns 2 and 4 of Table 7 show that the impact of farmland ownership is negative for small farms (0.5 to 1.624 acres) but is positive for large farms (1.625 acres or more). Though these effects are not statistically significant, this pattern of effects suggests that for households with large farmland the productivity of children's work might outweigh the (positive) income effect.

Distance to the nearest urban center (thana headquarters) reflects the opportunity for non-farm work for household members. This variable has a small but significantly positive impact on girls' labor force participation. Since it is more likely that potential (non-agricultural) earnings of male members of the household are affected by the distance to the thana headquarters, the effect on girls' labor force participation can be viewed as the effect of reduced earnings of the household.

Father's schooling acts as a proxy for his earnings. As expected, increases in father's schooling are generally associated with lower labor force participation by boys and girls. Father's schooling significantly affects boys only if father has more than primary school education but for girls the effect peters out at higher levels of father's schooling. The fact that only post primary schooling of the father affects boys' labor force participation suggests that when father's income earning potential is low, boys' work remains attractive for the family.

Mother's schooling captures more than just her potential earnings. Empirical evidence consistently shows that children benefit from mother's schooling suggesting that schooling raises her non-market productivity. These effects are reflected in children's labor force participation as well. Mother's schooling is associated with a reduction in labor force participation of boys and girls but only mother's primary schooling shows statistically significant impact on boys' labor force participation.[29]

Columns 5 and 6 report estimates of school enrollment equation for boys and columns 7 and 8 report estimates of the school enrollment equation for girls. The estimates reported in columns 5 and 7 do not include controls for child's household or village characteristics. These results show that the intensive family planning program had a small but negative impact on school enrollment of boys and girls. When additional controls are introduced, the program impact on both boys' and girls' enrollment is remains small and negative and statistically not significant. From the discussion in section 4, these uncompensated program effects are not indicative of the compensated substitution effect since they include income effects. If schooling and fertility are compensated substitutes (as evidence in literature suggests) then the sign of the

[29] In their district level analysis, Rosenzweig and Evenson (1977) found that it was the proportion of women in the district with higher education that was associated with decline in labor force participation by boys and girls.

program effects on school enrollment suggest the dominance of the income effect over the substitution effect.

The lack of significance of the cross-effect on schooling is similar to findings from other studies in literature. As noted in section 2, most estimates of the effect of family planning programs on schooling obtained in literature tend not to be statistically significant. Foster and Roy (1997) estimated the difference-in-differences estimates of the program impact on completed years of schooling for children aged 8-15 by using census data from 1974 and 1982 and survey data from 1990. They found that the program had significant impact on years of schooling only by 1990. Aside from differences in methodology and in specification of the equations, the results obtained here could differ from those obtained by Foster and Roy due to government school reform efforts. [30] It is likely that the program impact on schooling had been eliminated by 1996 (when the MHSS was fielded) due to government's school reforms program. Starting in 1990, the government introduced countrywide school reform program that aimed at increasing primary school enrollment. The MHSS survey of primary schools in the study area shows that almost all the elements of the government education program were in effect in the study area by 1996 (free textbooks and uniforms, no tuition fees and so on).

Among the proxies for household income, farmland ownership and father's schooling show positive effects on school enrollment of both boys' and girls' suggesting that household income is an important determinant of school attendance in Matlab. Interestingly, small farms are associated with significantly higher school enrollment of boys while large farms are associated with significantly higher enrollment of girls. Distance to the thana headquarters does

[30] Differences in the type of data used might also affect the comparability of results. The estimates from the Foster and Roy study are based mainly on census data while the estimates obtained here are based on survey data and are obtained from regressions that apply sampling weights.

not show statistically significant effects. Effect of father's schooling shows a generally positive effect on boys' and girls' enrollment. While the effect is statistically significant for girls for all categories of father's schooling, for boys, only father's secondary school education has a significant impact on enrollment.

There is ample evidence in literature showing the positive effect of parents' schooling on children's schooling and this effect is found here as well (Strauss and Thomas, 1995). Mother's schooling shows a positive effect on school enrollment of boys and girls but the effect is not statistically significant for boys. For girls, only mother's secondary schooling has a significant positive impact, raising probability of current enrollment by 9%.[31] As seen in columns 6 and 8, the effects of mother's schooling and father's schooling on girls' current enrollment tend to be larger than the effects on boys' enrollment. This can be contrasted with Thomas (1994). He found that mother's schooling had a significant impact on daughters' nutrition (measured by height) relative to sons' nutrition while father's schooling had a larger impact on sons' nutrition relative to daughters' nutrition.

7.2 Two Stage Estimates of Child Labor Force Participation and Enrollment

Tables 8 and 9 reports the results for labor force participation and enrollment by gender. In columns 1 and 4 of both tables, conditional estimates are reported where boys' and girls' labor force participation and enrollment equations are estimated with mother's fertility assumed to be exogenous. The measure of fertility used here is children ever born to mother. Columns 2 and 3

[31] This pattern of effects can be contrasted with that obtained by Behrman, Foster and Rosenzweig (1997). In their test of non-market returns to women's schooling in rural India, Behrman, Foster and Rosenzweig found that mother's literacy and not primary school completion significantly raised average daily study hours of children (hours in school + hours spent in homework).

and 5 and 6 of Tables 8 and 9 report 2SCML estimates where mother's fertility is instrumented with program treatment. First stage fertility equations for boys and girls are reported in columns 2 and 5 of Tables 8 and 9. Columns 3 and 6 in the two tables report second stage probit estimates. The probit estimates are obtained using the two stage conditional maximum likelihood (2SCML) method developed by Rivers and Vuong (1988) where residual from the first stage reduced form fertility equation is included in the second stage regression along with fertility.

The estimates of children's labor force participation and enrollment equations conditional on mother's fertility show statistically insignificant effect of fertility on the two outcomes for both boys and girls. Since mother's fertility is potentially endogenous, the 2SCML estimation would be appropriate. The first stage regression estimates reported in columns 2 and 5 of both tables show that residence in treatment area village explains a significantly large percentage of the variation in fertility. The last row of the tables 8 and 9 reports Rivers and Vuong's conditional likelihood ratio statistic which tests for potential endogeneity of fertility in the labor force participation equations. The null hypothesis of exogeneity of fertility variable is rejected only for boys' labor force participation but not for girls' labor force participation or for boys' and girls' enrollment.

Variables other than mother's fertility show the same pattern of effects as the reduced form estimates reported in table 7. The conditional and 2SCML estimates of girls' labor force participation and boys' and girls' school enrollment equation show no statistically significant impact of mother's fertility. However, 2SCML estimates of boys' labor force participation show that increase in mother's fertility significantly reduces boys' labor force participation. From the first stage regression for boys, program exposure lowers fertility by 0.84 births (Column 2). The 2SCML estimate of boys' labor force participation equation implies that probability of participating decreases by 13 percentage points per birth. Taken together, these two effects indicate that the program increased labor force participation by boys by 11 percentage points (-.844 $\times$ -.129). This is very close to the marginal effect obtained from the reduced form probit equation for labor force participation of boys (Table 7, column 2). Repeating this exercise for girls' labor force participation and for girls' and boys' school enrollment also yields estimates of program impact that are similar to those obtained from the corresponding reduced form probit estimates.

8. Conclusions

The Matlab family planning program reduced fertility in treatment villages. The estimates indicate that 18 years after the program was introduced, mean lifetime fertility of women who received the program was 0.55 births below that of women who did not receive the program. This translates into a reduction in fertility of about 13%. Previous evaluations of the program have shown that the program significantly reduced birth rates indicating that the program increased birth spacing. The estimated 13% reduction in lifetime fertility associated with the program that was estimated in this paper can be interpreted as the cumulative effect of the program's impact on birth spacing over a woman's reproductive life.

The estimates also suggest that mother's program exposure did not affect boys' and girls' school enrollment. Foster and Roy (1997) estimated that by 1990 the Matlab program had significantly raised completed years of schooling. However, this study found that by 1996 the program did not have a significant impact on children's school enrollments. This could be attributed to the introduction of school reforms by the government starting 1990. Importantly, the results found here demonstrate that by influencing mother's fertility, the program influences labor force participation by children. While the impact on girls' labor force participation is statistically not significant, the impact on boys' labor force participation is significant and implies that the program raised boys' labor force participation by 11%. Literature has paid little attention to the impact of the program on labor supply of children, despite the evidence that for households in this setting fertility and productive work by children are highly correlated. The Slutsky equation derived from the simple household demand model suggests that large child labor supply responses to changes in real income could be responsible for this result.

The estimates of program impact obtained here do not take into account dynamic effects of the program. The program and cross-program impacts are estimated using data from 1996 when the program had been in place for 18 years. Over time the program may have had general equilibrium effects that influenced the estimated program and cross-program impacts obtained. For instance, by reducing fertility in the treatment villages, the program might have increased child wages. Findings from the Matlab family planning program experiment reported here also suffer from problems of external validity that are typically associated with applying the lessons learnt from such programs to other contexts. Both the type and intensity of the program intervention and the economic conditions prevailing in Matlab make it difficult to generalize the results obtained here.

References

Aziz, K. M. A. and W. H. Mosley, 1994, Historical perspective and cultural background of the Matlab project, in V. Fauveau, ed., Matlab: Women, Children and Health, ICDDR,B Special Publication No. 35, 29-50.

Basu, Kaushik and Pham Hoang Van, 1998, The economics of child labor, American Economic Review, 88(3), 412-427.

Barrera, Albino, 1990, The role of maternal schooling and its interaction with public health programs in child health production, Journal of Development Economics, 32, 69-91.

Burtless, G., 1995, The case for randomized field trials in economic and policy research, Journal of Economic Perspectives, 9(2), 63-84.

Cain, Mead, 1977, The economic activities of children in a village in Bangladesh, Population and Development Review, 3(3), 201-227.

Cain, Mead and A.B.M. Khorshed Alam Mozumder, 1981, Labour market structure and reproductive behavior in rural South Asia, in Gerry Rodgers and Guy Standing, eds., Child work, poverty and underdevelopment, Geneva: International Labour Organization, 1981, 245-287.

Chowdhury, A. I. And J. F. Phillips, 1984, Socio-economic status differentials among currently married women of reproductive age for treatment and control areas of the Family Planning-Health Services Project from the 1974 Matlab census, Journal of Family Welfare, 31.

Deaton, Angus, 1997, The analysis of household surveys: A microeconometric approach to development policy, Johns Hopkins University Press, Baltimore, Maryland.

Duraisamy, P. and Malathy, R., 1991, Impact of public programs on fertility and gender specific investment in human capital of children in rural India: Cross sectional and time series analyses, in T.P. Schultz, ed., Research in Population Economics, 7, Greenwich, CT, JAI Press, 157-187.

Fauveau, V. and J. Chakraborty, 1994, Family planning and maternal and child health services in Matlab, in V. Fauveau, ed., Matlab: Women, Children and Health, ICDDR,B Special Publication No. 35, 89-107.

Foster, A. and N. Roy, 1997, The dynamics of education and fertility: Evidence from a family planning experiment, mimeo, Department of Economics, University of Pennsylvania.

Freedman, R. and J. Y. Takeshita, 1969, Family Planning in Taiwan, Princeton University Press, Princeton, New Jersey.

Gertler, P. and J. Molyneaux, 1994, How economic development and family planning programs combined to reduce Indonesian fertility, 31(1), 33-63.

Gertler, P., L. Locay and W. Sanderson, 1987, Are user fees regressive? The welfare implications of health care financing proposals in Peru, Journal of Econometrics, 36, 67-88.

Hossain, S., 1989, Effect of public programs on family size, child education and health, Journal of Development Economics, 30, 145-158.

Khandker, S. and H. A. Samad, 1995, Education achievements and school efficiency in rural Bangladesh, Bangladesh Development Studies, 23(1&2), 1-27.

Koenig, M., U. Rob, M. A. Khan, J. Chakraborty and V. Fauveau, 1992, Contraceptive use in Matlab, Bangladesh in 1990: Levels, trends and explanations, Studies in Family Planning, 23(6), 352-364.

Phillips, J. F., 1994, Matlab and the Bangladesh family planning and health program, in V. Fauveau, ed., Matlab: Women, Children and Health, ICDDR,B Special Publication No. 35, 415-435.

Phillips, J. F., R. Simmons, M. Koenig and J. Chakraborty, 1988, Determinants of reproductive change in a traditional society: Evidence from Matlab, Bangladesh, Studies in Family Planning, 19(6), 313-334.

Phillips, J. F., W. Stinson, S. Bhatia, M. Rahman and J. Chakraborty, 1982, The demographic impact of family planning – health services project in Matlab, Bangladesh, Studies in Family Planning, 13(5), 131-140.

Pitt, M., M. Rosenzweig and D. Gibbons, 1993, The determinants and consequences of the placement of government programs in Indonesia, World Bank Economic Review, 7, 319-348.

Rahman, Omar, J. Menken, A. Foster, C. E. Peterson, M. N. Khan, R. Kuhn, P. Gertler, ICDDRB, Mitra and Associates, 1999, The 1996 Matlab Health and Socioeconomic Survey: Overview and User's Guide, RAND, DRU-2018/1-NIA, Santa Monica, CA.

Ray, R., 2000, Analysis of child labour in Peru and Pakistan, Journal of Population Economics, 13, 3-19.

Rivers, D. and Q. H. Vuong, 1988, Limited information estimators and exogeneity tests for simultaneous probit models, Journal of Econometrics, 39, 347-366.

Rosenzweig, M. and R. Evenson, 1977, Fertility, schooling and economic contribution of children in rural India: An econometric analysis, Econometrica, 45(5), 1065-1079.

Rosenzweig, M, and K. Wolpin, 1980, Testing the quantity-quality fertility model: The use of twins as a natural experiment, Econometrica, 48(1), 227-240.

Rosenzweig, M, and K. Wolpin, 1982, Government interventions and household behavior in a developing country: Anticipating the unanticipated consequences of social programs, Journal of Development Economics, 10, 209-225.

Rosenzweig, M. and K. Wolpin, 1986, Evaluating the effects of optimally distributed public programs: Child health and family planning interventions, American Economic Review, 76(3), 470-482.

Rosenzweig, M. and K. Wolpin, 1988, Migration selectivity and the effects of public programs, Journal of Public Economics, 37, 265-289.

Rosenzweig, M. and K. Wolpin, 2000, Natural “natural experiments” in economics, Journal of Economic Literature, 38, 827-874.

Rosenzweig, M. and T. P Schultz, 1982, Child mortality and fertility in Colombia: Individual and community effects, Health Policy and Education, 2, 305-348.

Rosenzweig, M. and T. P. Schultz, 1989, Schooling, information and nonmarket productivity: Contraceptive use and its effectiveness, International Economic Review, 30(2), 1989, 457-477.

Samad, A., 2000, Development of primary education in Bangladesh: The ways ahead, Bangladesh Development Studies, 26(4), 39-68.

Schultz, T. P., 1974, Fertility determinants: A theory, evidence and an application to policy evaluation, R 1016-RF/AID, The Rand Corp., Santa Monica, CA, April.

Schultz, T. P., 1998, Population programs: Measuring their impact on fertility and the personal distribution of their effects, Journal of Policy Modeling, 10 (1), 113-139.

Schultz, T. P., 1992, Assessing family planning cost-effectiveness: applicability of individual demand-program supply framework, in J. F. Phillips and J. A. Ross, ed., Family planning programmes and fertility, Oxford University Press, New York.

Schultz, T. P., 1994, Human capital, family planning and their effects on population growth, American Economic Review, 84(2), 255–260.

Schultz, T. P., 1997, Demand for children in low income countries, in M. R. Rosenzweig and O. Stark, ed., Handbook of Population and Family Economics, 1A, Amsterdam: North Holland.

StataCorp., 1999, Stata Reference Manual: Release 6,Volume 4, Stata Press, College Station, TX.

Strauss, J., 1990, Households, communities and preschool child nutrition outcomes: Evidence from rural Cote de Ivoire, Economic Development and Cultural Change, 38(2) 231-261.

Thomas, D., J. Strauss and M. Henrique, 1990, How does mother’s education affect child height?, Journal of Human Resources, 26(2), 183-211.

Waldman, Amy, 2003, In rural part of Bangladesh, an ideal lab, New York Times, March 26, 2003.

Wooldridge, Jeffrey, 2002, Econometric analysis of cross section and panel data, MIT Press, Cambridge, Massachusetts.

Table 1: A Check of Random Program Placement

	Pre-Program Cohort Wife Aged 40 or older in 1978 (58+ in 1996)		
	Treatment (N=375)	Control (N=393)	Difference (p value)
Variable	Mean (Std. Dev.)	Mean (Std. Dev.)	
Children Ever Born	7.30 (2.67)	7.12 (2.50)	0.18 (0.50)
Hindu	0.18 (0.38)	0.04 (0.19)	0.14 (0.00)
Wife's Education	0.52 (1.51)	0.57 (1.55)	-0.06 (0.69)
Husband's Education	2.27 (3.42)	2.17 (3.13)	0.10 (0.78)
Farmland (0.5 acres – 1.624 acres)	0.32 (0.47)	0.27 (0.44)	0.05 (0.27)
Farmland (1.625 acres or more)	0.16 (0.37)	0.27 (0.44)	-0.10 (0.02)
Distance to Thana Headquarters (Kms)	5.84 (4.07)	5.36 (4.79)	0.48 (0.52)

Notes: Based on sample of ever married women. Reported statistics are weighted to correct for unequal sampling probabilities.

Table 2: Descriptive Statistics, Ever Married Women Sample

	Post-Program Cohort
	Wife Aged 39 or younger in 1978 (15-57 in 1996) (N=4,124)
Variable	Means (Std. Dev.)
Children Ever Born	4.29 (2.70)
Resides in Treatment Village	0.56 (0.50)
Age	36.53 (10.64)
Hindu	0.13 (0.33)
Wife's Education	2.21 (3.01)
Husband's Education	3.33 (3.79)
Farmland (0.5 acres – 1.624 acres)	0.26 (0.44)
Farmland (1.625 acres or more)	0.12 (0.32)
Distance to Thana Headquarters (Kms)	5.77 (4.59)

Notes: Based on sample of ever married women. Reported statistics are weighted to correct for unequal sampling probabilities.

Table 3: Means of Variables in Ever Married Women Sample, By Program

	Post-Program Cohort		
	Wife Aged 39 or younger in 1978 (15-57 in 1996)		
	Treatment (N=2084)	Control (N=2040)	Difference (p value)
Variable	Mean (Std. Dev.)	Mean (Std. Dev.)	
Children Ever Born	4.12 (2.56)	4.50 (2.85)	-0.39 (0.00)
Hindu	0.17 (0.38)	0.06 (0.24)	0.11 (0.00)
Wife's Education	2.17 (2.99)	2.26 (3.04)	-0.08 (0.64)
Husband's Education	3.39 (3.83)	3.25 (3.74)	0.14 (0.54)
Farmland (0.5 acres – 1.624 acres)	0.26 (0.44)	0.25 (0.43)	0.01 (0.57)
Farmland (1.625 acres or more)	0.11 (0.31)	0.13 (0.34)	-0.02 (0.21)
Distance to Thana Headquarters (Kms)	5.99 (4.51)	5.50 (4.67)	0.49 (0.43)

Notes: Based on sample of ever married women. Reported statistics are weighted to correct for unequal sampling probabilities.

Table 4: Descriptive Statistics, Children Sample

	Boys (N=1335)	Girls (N=1165)
Variable	Mean (Std. Dev.)	Mean (Std. Dev.)
Currently Working	0.39 (0.49)	0.33 (0.47)
Currently Enrolled	0.80 (0.40)	0.86 (0.34)
Resides in Treatment Village	0.52 (0.50)	0.58 (0.49)
Children Ever Born to Mother	5.55 (2.18)	5.75 (2.09)
Age	12.98 (2.03)	12.82 (1.99)
Hindu	0.09 (0.29)	0.10 (0.30)
Mother's Age	39.22 (6.56)	39.24 (6.60)
Mother's Education: Primary or less	0.32 (0.47)	0.31 (0.46)
Mother's Education: Secondary or higher	0.10 (0.30)	0.09 (0.28)
Father's Education: Primary or less	0.30 (0.46)	0.28 (0.45)
Father's Education: Secondary	0.21 (0.41)	0.23 (0.42)
Father's Education: More than Secondary	0.04 (0.20)	0.05 (0.22)
Farmland (less than 0.5 acre)	0.63 (0.48)	0.62 (0.48)
Farmland (0.5 acres – 1.624 acres)	0.26 (0.44)	0.26 (0.44)
Farmland (1.625 acres or more)	0.11 (0.32)	0.11 (0.32)
Distance to Thana Headquarters (Kms)	5.65 (4.75)	5.96 (4.60)

Notes: Based on sample of children aged 10 – 16 with mothers who are 57 or younger. Reported statistics are weighted to correct for unequal sampling probabilities.

Table 5: Means of Variables in Children Sample, By Sex and Program

	Boys			Girls		
	Treatment (N=635)	Control (N=700)	Difference (P value)	Treatment (N=592)	Control (N=573)	Difference (P value)
Variable	Mean (Std. Dev.)	Mean (Std. Dev.)		Mean (Std. Dev.)	Mean (Std. Dev.)	
Currently Working	0.43 (0.50)	0.35 (0.48)	0.08 (0.03)	0.33 (0.47)	0.32 (0.47)	0.01 (0.81)
Currently Enrolled	0.78 (0.41)	0.82 (0.39)	-0.03 (0.31)	0.85 (0.35)	0.88 (0.33)	-0.03 (0.38)
Mother's Fertility	5.08 (1.96)	6.05 (2.28)	-0.98 (0.00)	5.41 (2.03)	6.21 (2.10)	-0.80 (0.00)
Age	13.01 (2.06)	12.95 (2.00)	0.06 (0.70)	12.83 (1.94)	12.81 (2.05)	0.02 (0.89)
Hindu	0.13 (0.34)	0.05 (0.21)	0.09 (0.00)	0.15 (0.35)	0.03 (0.18)	0.11 (0.00)
Mother's Age	39.00 (6.24)	39.44 (6.87)	-0.44 (0.44)	38.93 (6.17)	39.65 (7.12)	-0.72 (0.22)
Mother's Education: Primary or less	0.31 (0.46)	0.34 (0.47)	-0.03 (0.52)	0.34 (0.47)	0.28 (0.45)	0.06 (0.14)
Mother's Education: Secondary or higher	0.13 (0.33)	0.08 (0.27)	0.05 (0.04)	0.08 (0.27)	0.09 (0.29)	-0.02 (0.49)
Father's Education: Primary or less	0.29 (0.45)	0.30 (0.46)	-0.02 (0.71)	0.26 (0.44)	0.30 (0.46)	-0.03 (0.39)
Father's Education: Secondary	0.22 (0.42)	0.21 (0.41)	0.02 (0.66)	0.24 (0.43)	0.23 (0.42)	0.01 (0.84)
Father's Education: More than Secondary	0.06 (0.23)	0.02 (0.15)	0.04 (0.01)	0.05 (0.23)	0.04 (0.20)	0.01 (0.56)
Farmland (0.5 acres – 1.624 acres)	0.25 (0.43)	0.27 (0.44)	-0.02 (0.68)	0.26 (0.44)	0.27 (0.44)	-0.01 (0.81)
Farmland (1.625 acres or more)	0.09 (0.29)	0.13 (0.34)	-0.04 (0.14)	0.11 (0.32)	0.11 (0.31)	0.00 (0.96)
Distance to Thana Headquarters (Kms)	5.81 (4.78)	5.49 (4.70)	0.32 (0.48)	5.84 (4.42)	6.11 (4.83)	-0.27 (0.57)

Notes: Based on sample of children aged 10 – 16 with mothers who are 57 or younger. Reported statistics are weighted to correct for unequal sampling probabilities.

Table 6: Effect of Program on Fertility

	Least Squares Estimates* (robust t statistics)			Tobit Model Marginal Effects** (robust z statistics)		
	(1)	(2)	(3)	(4)	(5)	(6)
Resides in Treatment Village	-0.641 (9.59)	-0.581 (8.89)	-0.619 (6.96)	-0.613 (9.46)	-0.553 (8.68)	-0.583 (6.85)
Wife's Age	0.433 (22.33)	0.427 (22.47)	0.425 (22.51)	0.503 (22.56)	0.497 (22.89)	0.496 (22.90)
$(\text{Wife's Age})^2$	-0.003 (12.09)	-0.003 (12.35)	-0.003 (12.35)	-0.004 (14.00)	-0.004 (14.38)	-0.004 (14.38)
Hindu		-0.362 (4.32)	-0.144 (0.71)		-0.363 (4.39)	-0.161 (0.80)
Treatment Village × Hindu			-0.294 (1.34)			-0.274 (1.27)
Wife's Education		-0.072 (6.82)	-0.087 (6.03)		-0.073 (6.81)	-0.086 (6.01)
Treatment Village × Wife's Education			0.029+ (1.75)			0.025 (1.51)
Husband's Education		-0.006 (0.70)	-0.006 (0.74)		-0.006 (0.79)	-0.007 (0.83)
Farmland (0.5 acres – 1.624 acres)		0.162 (2.07)	0.161* (2.06)		0.146 (1.90)	0.145 (1.90)
Farmland (1.625 acres or more)		0.259 (2.62)	0.260** (2.63)		0.250 (2.58)	0.251 (2.60)
Distance to Thana Headquarters (Kms)		0.003 (0.47)	0.003 (0.46)		0.003 (0.45)	0.003 (0.43)
Obs	4124	4124	4124	4124	4124	4124
R-squared	0.56	0.57	0.57			
σ (Std. Error)				1.87 (0.031)	1.85 (0.031)	1.85 (0.031)
Proportion Zero Births	0.06	0.06	0.06	0.06	0.06	0.06

Notes: Based on sample of ever married women aged 15-57.
* Robust t-statistics.
**Marginal effects evaluated at sample means. Robust z-statistics.

Table 7: Effect of Program on Children's Labor Force Participation and Enrollment, Reduced Form Estimates

	Labor Force Participation				Enrollment			
	Probit MLE Marginal Effects* (robust z statistics)				Probit MLE Marginal Effects* (robust z statistics)			
	Boys		Girls		Boys		Girls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Resides in Treatment Village	0.085 (2.12)	0.108 (2.69)	0.013 (0.33)	0.009 (0.24)	-0.028 (0.88)	-0.026 (0.86)	-0.033 (1.18)	-0.015 (0.67)
Age	0.032 (0.20)	-0.009 (0.06)	-0.063 (0.48)	-0.078 (0.60)	0.138 (1.19)	0.166 (1.52)	0.319 (3.13)	0.266 (3.25)
$(Age)^2$	0.002 (0.36)	0.004 (0.62)	0.004 (0.83)	0.005 (0.99)	-0.007 (1.64)	-0.008 (1.96)	-0.013 (3.41)	-0.011 (3.53)
Hindu		-0.076 (1.12)		0.026 (0.28)		-0.025 (0.43)		-0.122 (2.89)
Mother's Age		0.047 (0.99)		-0.010 (0.30)		-0.065 (2.38)		-0.019 (1.05)
$(Mother's Age)^2$		-0.001 (0.94)		0.000 (0.26)		0.001 (2.28)		0.000 (0.99)
Mother's Education: Primary or less		-0.091 (1.71)		-0.013 (0.27)		0.041 (1.09)		0.024 (0.78)
Mother's Education: Secondary or higher		-0.143 (1.51)		-0.111 (1.49)		0.059 (1.02)		0.092 (3.25)
Father's Education: Primary or less		0.025 (0.50)		-0.112 (2.43)		0.036 (1.00)		0.045 (1.96)
Father's Education: Secondary		-0.124 (2.06)		-0.099 (1.76)		0.078 (1.74)		0.089 (2.84)
Father's Education: More than Secondary		-0.187 (1.99)		-0.077 (0.72)		0.114 (1.60)		0.078 (2.62)

Table 7 Continued

	Labor Force Participation				Enrollment			
	Probit MLE Marginal Effects* (robust z statistics)				Probit MLE Marginal Effects* (robust z statistics)			
	Boys		Girls		Boys		Girls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Farmland (0.5 acres – 1.624 acres)		-0.048 (0.86)		-0.012 (0.23)		0.098 (3.02)		0.033 (1.37)
Farmland (1.625 acres or more)		0.049 (0.79)		0.043 (0.60)		0.046 (0.80)		0.056 (1.82)
Distance to Thana Headquarters (Kms)		-0.003 (0.70)		0.008 (2.06)		0.000 (0.04)		-0.004 (1.61)
Obs	1335	1335	1165	1165	1335	1335	1165	1165

Notes: Based on sample of children aged 10 – 16 (mothers aged 57 or younger).
*Weighted Maximum Likelihood estimates that adjust for unequal sampling probabilities. Robust z-statistics correct for unequal sampling probabilities and clustering of observations within baris.

Table 8: Effect of Program on Children's Labor Force Participation, 2SCML Estimates

	Boys			Girls		
		2SCML Estimates			2SCML Estimates	
		First Stage**	Second Stage***		First Stage**	Second Stage***
	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects
	(1)	(2)	(3)	(4)	(5)	(6)
Resides in Treatment Village		-0.844 (6.24)			-0.665 (4.75)	
Mother's Fertility	-0.011 (0.89)		-0.129 (2.62)	0.007 (0.62)		-0.014 (0.23)
Residual from 1st Stage			0.125 (2.46)			0.022 (0.36)
Age	-0.019 (0.12)	-0.001 (0.00)	-0.009 (0.05)	-0.072 (0.55)	-0.439 (0.97)	-0.083 (0.60)
$(Age)^2$	0.004 (0.68)	-0.004 (0.23)	0.003 (0.51)	0.005 (0.95)	0.015 (0.84)	0.005 (0.96)
Hindu	-0.058 (0.83)	-0.030 (0.16)	-0.080 (1.07)	0.032 (0.34)	-0.173 (0.66)	0.024 (0.25)
Mother's Age	0.057 (1.20)	0.388 (3.02)	0.097 (1.80)	-0.011 (0.35)	0.383 (3.66)	-0.004 (0.10)
$(Mother's\ Age)^2$	-0.001 (1.11)	-0.002 (1.36)	-0.001 (1.36)	0.000 (0.26)	-0.002 (1.72)	0.000 (0.16)
Mother's Education: Primary or less	-0.092 (1.75)	-0.023 (0.16)	-0.094 (1.66)	-0.013 (0.26)	0.043 (0.24)	-0.013 (0.24)
Mother's Education: Secondary or higher	-0.135 (1.38)	-0.543 (2.58)	-0.200 (2.05)	-0.108 (1.42)	-0.629 (2.28)	-0.118 (1.33)
Father's Education: Primary or less	0.025 (0.51)	-0.294 (1.94)	-0.013 (0.26)	-0.112 (2.43)	-0.064 (0.36)	-0.112 (2.35)
Father's Education: Secondary	-0.122 (2.05)	-0.340 (2.02)	-0.164 (2.68)	-0.098 (1.76)	-0.093 (0.44)	-0.100 (1.78)
Father's Education: More than Secondary	-0.174 (1.80)	-0.353 (1.38)	-0.220 (2.18)	-0.077 (0.73)	-0.123 (0.31)	-0.080 (0.71)
Farmland (0.5 acres – 1.624 acres)	-0.052 (0.94)	0.155 (1.01)	-0.028 (0.49)	-0.012 (0.24)	-0.014 (0.08)	-0.012 (0.24)
Farmland (1.625 acres or more)	0.030 (0.49)	-0.012 (0.06)	0.047 (0.74)	0.043 (0.60)	-0.002 (0.01)	0.043 (0.57)
Distance to Thana Headquarters (Kms)	-0.003 (0.65)	-0.024 (1.12)	-0.006 (1.36)	0.008 (2.05)	0.001 (0.09)	0.008 (1.93)
Constant		-4.735 (1.38)			-2.202 (0.67)	

Table 8 Continued

	Boys			Girls		
		2SCML Estimates			2SCML Estimates	
		First Stage**	Second Stage***		First Stage**	Second Stage***
	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects
Observations	1335	1335	1335	1165	1165	1165
Log Likelihood	-777.41		-771.01	-697.06		-696.94
Conditional Likelihood Ratio Statistic (chi square p-value) (Rivers and Vuong, 1988)			12.8 (0.00)			0.24 (0.62)

Notes: Based on sample of children aged 10 – 16 (mothers aged 57 or younger). *Weighted Maximum Likelihood estimates that adjust for unequal sampling probabilities. Robust z-statistics correct for unequal sampling probabilities and clustering of observations within baris.
** Weighted Least Squares estimates that adjust for the unequal sampling probabilities. Robust t-statistics correct for unequal sampling probabilities and clustering of observations within baris.
*** Weighted Maximum Likelihood estimates that adjust for unequal sampling probabilities. Robust z statistics based on bootstrapped standard errors calculated using 1000 replications. Bootstrapping adjusted for sampling design. Mother's Fertility is treated as endogenous and identified by program treatment.

Table 9: Effect of Program on Enrollment, 2SCML Estimates

	Boys			Girls		
		2SCML Estimates			2SCML Estimates	
		First Stage**	Second Stage***		First Stage**	Second Stage***
	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects
	(1)	(2)	(3)	(4)	(5)	(6)
Resides in Treatment Village		-0.844 (6.24)			-0.665 (4.75)	
Mother's Fertility	-0.005 (0.55)		0.031 (0.80)	-0.001 (0.22)		0.022 (0.61)
Residual from 1st Stage			-0.037 (0.96)			-0.024 (0.66)
Age	0.170 (1.56)	-0.001 (0.00)	0.166 (1.47)	0.262 (3.25)	-0.439 (0.97)	0.274 (3.06)
$(Age)^2$	-0.008 (2.00)	-0.004 (0.23)	-0.008 (1.87)	-0.011 (3.54)	0.015 (0.84)	-0.011 (3.33)
Hindu	-0.031 (0.54)	-0.030 (0.16)	-0.024 (0.37)	-0.131 (3.12)	-0.173 (0.66)	-0.115 (2.42)
Mother's Age	-0.063 (2.34)	0.388 (3.02)	-0.076 (2.47)	-0.020 (1.07)	0.383 (3.66)	-0.028 (1.26)
$(Mother's\ Age)^2$	0.001 (2.28)	-0.002 (1.36)	0.001 (2.29)	0.000 (1.03)	-0.002 (1.72)	0.000 (1.11)
Mother's Education: Primary or less	0.041 (1.10)	-0.023 (0.16)	0.041 (1.05)	0.023 (0.74)	0.043 (0.24)	0.023 (0.67)
Mother's Education: Secondary or higher	0.054 (0.92)	-0.543 (2.58)	0.072 (1.11)	0.092 (3.25)	-0.629 (2.28)	0.094 (4.39)
Father's Education: Primary or less	0.035 (0.96)	-0.294 (1.94)	0.045 (1.16)	0.046 (1.99)	-0.064 (0.36)	0.046 (1.97)
Father's Education: Secondary	0.076 (1.70)	-0.340 (2.02)	0.087 (1.76)	0.089 (2.84)	-0.093 (0.44)	0.090 (2.62)
Father's Education: More than Secondary	0.110 (1.50)	-0.353 (1.38)	0.119 (1.49)	0.079 (2.61)	-0.123 (0.31)	0.079 (2.78)
Farmland (0.5 acres – 1.624 acres)	0.100 (3.06)	0.155 (1.01)	0.094 (2.66)	0.034 (1.39)	-0.014 (0.08)	0.033 (1.32)
Farmland (1.625 acres or more)	0.050 (0.88)	-0.012 (0.06)	0.047 (0.73)	0.056 (1.78)	-0.002 (0.01)	0.056 (1.55)
Distance to Thana Headquarters (Kms)	-0.000 (0.04)	-0.024 (1.12)	0.001 (0.30)	-0.004 (1.61)	0.001 (0.09)	-0.004 (1.50)
Constant		-4.735 (1.38)			-2.202 (0.67)	

Table 9 Continued

	Boys			Girls		
		2SCML Estimates			2SCML Estimates	
		First Stage**	Second Stage***		First Stage**	Second Stage***
	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects	Probit Marginal Effects*	Mother's Fertility	Probit Marginal Effects
Observations	1335	1335	1335	1165	1165	1165
Log Likelihood	-579.36		-578.33	-371.30		-370.78
Conditional Likelihood Ratio Statistic (chi square p-value) (Rivers and Vuong, 1988)			2.06 (0.15)			1.04 (0.31)

Notes: Based on sample of children aged 10 – 16 (mothers aged 57 or younger). *Weighted Maximum Likelihood estimates that adjust for unequal sampling probabilities. Robust z-statistics correct for unequal sampling probabilities and clustering of observations within baris.
** Weighted Least Squares estimates that adjust for the unequal sampling probabilities. Robust t-statistics correct for unequal sampling probabilities and clustering of observations within baris.
*** Weighted Maximum Likelihood estimates that adjust for unequal sampling probabilities. Robust z statistics based on bootstrapped standard errors calculated using 1000 replications. Bootstrapping adjusted for sampling design. Mother's Fertility is treated as endogenous and identified by program treatment.