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Does family planning program reduce inequality in contraceptive use, fertility and other health care utilization? Evidence from Bangladesh.

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Abstract:

Since the introduction of organized family planning programs almost 50 years ago, a large number of studies have examined the contribution of family planning programs in reducing fertility in economically disadvantaged countries. In addition, several studies have examined the concomitant benefits of family planning programs on infant and maternal mortality reduction. However, none of the studies has examined whether organized family planning programs can reduce inequality in contraceptive use and fertility level. Using nationally representative data from the Bangladesh Health and Demographic Survey, 1999-2000, we examine the effect family planning workers have on the reduction of inequality in contraceptive use and maternal and child health care (MCH) utilization. Our results suggest that family planning intervention provided by outreach workers significantly reduced inequality in modern contraceptive use (a concentration index of 0.095 (95% CI: 0.079-0.112) was reduced to 0.009 (95% CI: -0.009 to 0.24). In addition, the outreach programs significantly reduced inequality in maternal health care utilization. However, the effect of field workers on reducing inequality in fertility and unmet need was limited.

Introduction

The existence of significant socioeconomic differentials in contraceptive use, maternal and child health care utilization, childhood mortality and health status has been consistently shown by several empirical studies (Gupta 1990, 1997; Sastry 1997; Rutstein 1984; Preston 1975; Rodgers 1979). A study by Gwatkin and Deveshwar-Bahl (2001) in 42 developing countries found significant inequalities in immunization coverage by socioeconomic status. On average the proportion of children immunized was almost 30 percent higher among the richest population quintile compared to the poorest quintile (66% vs 38.5%, respectively). Gupta (1990) showed that economic status was one of the key determinants for the clustering of childhood deaths in rural India (12.6% of women accounted for 62.2% of all child deaths), and Guo (1993) found that most of the child mortality in Guatemala is explained by socio-economic status and mothers education. The examination of health inequality in Bangladesh by Gwatkin et al. (2000) found extensive inequality in infant and under five mortality, child nutritional status, fertility rates, immunization coverage, antenatal care visits, delivery care, and modern contraceptive use. The analysis of Demographic and Health Survey (DHS) data in 41 developing countries also show significant inequality in fertility levels by socioeconomic status: overall total fertility level (TFR) is almost double in the poorest women (TFR of 6.0), compared to the women in wealthiest group (TFR of 3.1) (Gillespie and Radloff, 2003).

Reduction of health inequality is an important objective of health policy in each country (Gakidou and King, 2002; WHO, 1987). With the introduction of the "Health for All by 2000" movement in late 1970s, WHO highlighted the significance of reaching poor segments of the population and achieving equity in health globally. However, soon after the "Alma Ata Declaration" of WHO-UNICEF conference in 1978, the "primary health care" (PHC) programs aimed at achieving the goal of "Health for All" faced stiff competition with the targeted public health interventions, such as child survival and family planning programs, and failed to sustain their momentum. In developing countries, organized maternal and child health care (MCH) and family planning (FP) programs are now integral parts of health infrastructure, planning and policy. Although MCH programs selectively target clients (pregnant women, children under 5 years and their mothers), family planning programs are more universal and target all women of reproductive age.

Family planning programs were initiated immediately after World War II in developing countries with the prime objective of reducing population growth (Bouvier and Bertrand, 1999), subsequently, however, both publicly and privately supported family planning programs embraced the additional objectives of: (a) protecting the health of women and children, and (b) implementing the rights of couples to exercise control over their fertility (Salkever and Sirageldin, 1983). The 1994 International Conference on Population and Development (ICPD) in Cairo radically shifted the focus of FP programs from "demographic targets" to overall improvement and equity in reproductive health.

Since the introduction of organized family planning programs almost 50 years ago, contraceptive prevalence rate (CPR) is frequently used as a yardstick for measuring the success of family planning programs (Bouvier and Bertrand, 1999; Hermalin, 1997), and a large number of studies have examined the contribution of these programs in reducing fertility in economically disadvantaged countries (United Nations, 1979). In addition, several studies examined the concomitant benefits of family planning programs on infant and maternal mortality reduction (Puffer, 1993; Potts, 1986; Winikoff and Sullivan 1987; Fortney, 1987). However, none of the studies have examined whether organized family planning programs can reduce inequality and improve equity in contraceptive use and reproductive health - one of the goals underscored in the ICPD mandates.

Increasingly international donor communities and the UN organizations are emphasizing on inequality reduction from the perspectives of social justice, equity, and overall national development. The objective of this paper is to examine the effect of family planning programs on the reduction of inequality in contraceptive use, fertility, and health care in one of the developing countries - Bangladesh.

Data and Methods

Using nationally representative BDHS 1999/2000 data, this paper examines the effects of organized family planning programs in Bangladesh on inequality reduction in contraceptive use, fertility and, and other preventive health care services, such as antenatal and delivery care. Bangladesh is considered as a success story in improving contraceptive use prevalence rates and reducing fertility levels, even with limited economic development. Since the introduction of family planning programs in Bangladesh, field workers are playing a pivotal role in promoting contraceptive use. Family health workers' visits may have both direct and indirect effects. Health workers directly initiate the dialogue and advocacy for family planning, and they are often the sole suppliers of temporary contraceptive methods. Further, interaction with health workers may directly lead to increased knowledge and awareness, as well as indirectly provides an impetus for discussion with husbands. They may even initiate and promote other health initiatives through discussion of overall health benefits of maternal and child health care.

Measurement of socioeconomic status

For assessing the inequality in health and health care utilization related outcomes some measures of socioeconomic status (SES) are required. The literature on socioeconomic inequality contains several measures of SES, such as social class, educational level, income, dwelling size, consumption, and ownership of household assets (as measured by wealth index). In developing countries, income data are difficult to gather and of poor quality. Several studies have suggested that a "wealth index" measured from household assets as a score through principal component analysis (PCA) is quite robust and serves as a good proxy for SES (Filmer, and Pritchett, 2001; Bollen, Glanville, and Stecklov, 2001). Wagstaff and Watanabe (2002) showed that inequality in malnutrition whether measured by wealth index or consumption – a direct measurement of economic condition – provide similar degrees of inequality magnitudes. Houweling, Kunst, and Mackenbach (2003), however, suggested that the sensitivity of the wealth index is significantly dependent upon the selection of asset indicators. Currently, wealth index is widely used for inequality studies in developing countries. We also used wealth index to stratify respondents in SES quintiles based on principal component analysis of domestic assets and household possessions. The lowest quintile indicates the poorest group and the highest quintile indicates the richest group.

Estimation of health inequality

Economists have developed several summary indices for income and health inequality, such as the Gini coefficient, relative index of inequality (RII), index of dissimilarities and concentration index (Wagstaff, Paci and van Doorslaer 1991). Gakidou and King, (2000, 2002) used beta-binomial regression models to estimate health inequality of childhood mortality in 50 developing countries. We used a concentration index to estimate the magnitude of inequality. The concentration index is an extension of the Gini coefficient and Wagstaff et al. (1991) suggested that it is a more attractive measure of health inequality and has the advantage of demonstrating the extent of inequality graphically by a concentration curve which is similar to a Lorenz curve that is widely used in income inequality literature.

We illustrate the theory behind the concentration index by presenting concentration curves, *L(p)* in Fig. 1. In the graph, the cumulative share (in %) of health on the *y- axis* is ploted against the cumulative proportion of population ranked by income (a common measurement of economic status) on the *x-axis*. If there is no income related inequality in health the poor will have the same share of health outcome as the rich. As an example, if k% of the population ranked by economic status accounts for the k% of health care utilization in the whole population, the concentration curve coincides with a 45^0 diagonal line and suggests that there is no income related inequality. If poor people are less healthy than the rich, the concentration curve will lie below the diagonal line (slow rise at the beginning of x-axis, and rapid rise later). Conversely, if adverse health is more concentrated in among rich individuals, the concentration curve will lie above the diagonal (rapid rise at the beginning and slow rise later).

Mathematically, the concentration index (CI) is defined as twice the area between the concentration curve and the diagonal:

$$CI = 1 - 2\int_0^1 L(x)dx$$

When there is no inequality, C equals zero. The value of the concentration index theoretically ranges between –1 to +1. A negative value suggests that the curve lies above the diagonal, and a positive value suggests the opposite.

Based on individual data, *CI* can be measured by (Kakwani et al., 1997):

$$CI = \frac{2}{n.\mu}\sum_{i=1}^{n} y_i R_i - 1$$

where y is the health and behavioral outcome, μ is the mean of y, R_i is the fractional rank of the *i-th* individual in the wealth asset distribution (on the continuum scale of socioeconomic status measurement).

Kakwani et. al. (1997) suggested a method of standardizing the concentration index with other confounding and control variables. We employed a “convenience regression” method for estimating concentration index (CI), which adjusts the estimation for other controlling factors that are known to affect the health outcomes (e.g., contraceptive use, fertility and MCH care utilization) as confounding variables:

$$2\sigma_R^2\left[\frac{y_i}{y}\right] = \alpha + \beta R_i + \delta X + \varepsilon_i \, .$$

where σ^2 is the variance of the fractional rank, y_i and y are the individual level and population average of the health outcome respectively, and X is the vector of controlling covariates. The OLS estimator of β is equal to:

$$\hat{\beta} = \frac{2}{n.\mu}\sum_{i=1}^{n}(y_i - y)(R_i - \frac{1}{2})$$

and implies that β equals to the measured concentration index (CI) from individual data. Fitting the convenience regression model to the estimate with simple OLS yields the correct β, and thus estimates the correct concentration index, but the standard error is inaccurate because the fractional rank induces autocorrelation in the data. Standard errors estimated with autocorrelation are known to be very low. We have fitted the model with the Newey-West regression (Newey & West, 1994) technique which corrects for autocorrelation and provides more efficient standard error for *CI*.

Regression models:

Our primary objective is to check whether family planning programs, as measured by the outreach visitation intensities, reduce inequality in contraceptive use, fertility and other preventive health care utilization. It is [theoretically] possible to assess the effect of family planning programs by examining the difference between CI_{visit} and $CI_{novisit}$ by fitting a convenience regression on the difference between two groups (i.e., on R_{visit} - $R_{novisit}$, rather than on R) as:

$$2\sigma_R^2\left[\frac{y_i}{y}\right] = \alpha + \beta(R_{visit} - R_{novisit}) + \delta X + \varepsilon_i \, .$$

However, women's are either visited by outreach workers or not visited, and as a result, R_{visit} -$R_{novisit}$ can not be observed empirically at an same individual level. Because of this couterfactual problem (Rubin, 1978), we have fitted multiplicative regression models to examine the effect of outreach family planning and health services on reducing the inequality in contraceptive use, fertility and health care. This was done by introducing interaction terms in the regression models to show the moderation effects of outreach service availability on the differentials in health care utilization by socioeconomic status:

$$E(y) = \alpha + \beta_1 SES + \beta_2 Wvisit + \beta_3 (SES * Wvisit) + \delta X \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

In this model specification, we expect a *negative* β_3 suggesting that the outreach workers visits reduce the differentials effect of SES.

When health outcome prevalence is low, there is little difference between an odds-ratio and a prevalence rate ratio; and therefore, logistic regression models have been widely used with binary outcomes in demographic studies because of its easy interpretation. However, in our case, several outcomes, such as the contraceptive prevalence rate (CPR), are quite high (~50%) and estimation of odds ratios with logistic regression provides poor approximation. Log-binomial models are preferred over logistic models for modeling prevalence rates (Skov et al., 1998) and we used log-binomial models, with appropriate variance correction for clustered data at community levels using the Taylor's linearization method. Generalized Poisson regression models were used for fertility, antenatal care, and institutional delivery care outcomes, where births and pregnancy associated care were treated as incidences.

Methods for reducing selectivity bias in workers' visits:

It is possible that field workers selectively visited the women who had positive attitude towards contraceptive use. Because of this possible selectivity family planning workers' visit to individuals may be endogenously determined and upwardly bias the estimates based on individual observations. To reduce the bias due to selectivity, we have used two alternative methods.

In econometric and social science literature, instrumental variable (IV) methods are widely used to reduce or eliminate the selectivity bias (Angrist, Imbens, and Rubin,

1996) and recently gained interests also in epidemiology (Greenland, 2000). In these methods instead of using the variable of interest (often termed *treatment variable* in the evaluation literature) subjected to selectivity, alternative instruments – variables which are related to the treatment variable, but not related to the outcome - are used. However, a major problem in practice is to identify the instrumental variables that are related to the treatment variable, but not to the outcome. There is no statistical test to empirically validate the selection of instrumental variables. In our case, it is also illusive to identify instrument variables that are related to family planning outreach visitations, but not related to outcome variables contraceptive use, fertility and health care. Alternatively, we have used two methods to reduce selection bias: (a) the ecological method (Wen and Kramer, 1999) in which individual responses are replaced with the clustered level aggregated values to reduce confounding at individual level, and (b) the propensity score method (Rosenbaum and Rubin, 1983) proposed for evaluation from observational studies.

The ecological method of aggregating individual responses at cluster levels was first proposed in epidemiological field by Wen and Kramer (1999) for reducing bias in "confounding by indication" (disease severity) in individual-level observational studies. Although ecological fallacy is a significant concern in epidemiological studies, Wen and Kramer suggested that, "The advantage of ecologic over individual-level observational studies in the assessment of intended treatment effects holds even if variations in disease severity, socioeconomic status, and other unmeasured factors are taken into account…." In sociological studies, Darlauf (2001) showed that endogenous effects can be measured from the observational studies by "group mean" outcome, and McQuestion (2002) applied "clustered level mean" values to address endogeneity. We have used "self-minus mean values" of outreach visitation at cluster level in which individual response was subtracted for estimating means so that the group means are [as much as possible] independent of the individual responses. This mean is often referred to as "jackknife mean," considering its similarity to jackknife variance as used in complex survey literature.

The propensity score matching method, proposed by Rosenbaum and Rubin(1983), has drawn significant interest in recent years for program evaluation based on observational studies when randomization is not possible or very costly, and increasingly used in econometric literature, social science study, epidemiology and health care research. In this method, the differential distribution in the characteristics between the treatment and non-treatment group is minimized by matching on the propensity scores. Influenced by the work of Cochrane (1968) that showed that stratified matching on five strata removes 90% of the bias due to the stratifying covariates, Rosenbaum and Rubin proposed to balance the treatment assignment with propensity scores for reducing selectivity bias. For subject *i*, the propensity score is the conditional probability of assignment to a particular treatment (in our case, the probability of being visited by outreach health workers, *Z=1*), compared to no visit (*Z=0*), given the vector of observed covariates, x_i:

$$e(x_i) = \Pr(Z_i = 1 \mid X_i = x_i)$$

Usually propensity scores are estimated with logistic regression in which the predicted probabilities of treatment assignment from the fitted models are assigned as the scores:

$$\hat{e}(x_i) = \Pr(Z_i = 1 \mid X_i = x_i) = \frac{\exp(x'\beta)}{1 + \exp(x'\beta)}$$

Under counterfactual arguments, the average treatment effect (ATE) is estimated from the balanced strata by:

$$\tau = E[Y_{1i} - Y_{0i} \mid Z = 1]$$

However, this method of estimating ATE is not suitable for our analysis as we are not interested to examine the treatment effect of whether outreach visitation increased contraceptive use or reduced fertility, rather to examine whether the outreach visitation reduced inequality in contraceptive use or fertility level. In other words, our interest is not in β_2, but in β_3 in Eq.1. As a result, we could not directly apply the propensity score matching method as proposed by Rosenbaum and Rubin.

Essentially, the propensity scores may be treated as (inverse selection) probability weights (Imbens, 2000) as "survey-design weights" are used for adjusting unequal probability sampling where:

$$\omega = \begin{cases} \dfrac{1}{e(x)} & if \;\; Z = 1 \\ \dfrac{1}{1 - e(x)} & if \;\; Z = 0 \end{cases}$$

We have used this estimator as normalized weights where sum of weights equal to one in Eq.1 to correct for the differentials in the selection probability between Z=1 and Z=0, given the observed covariates *Xs*.

In addition, we have fitted Eq.1 as conditional logistic regression models where the observations for Z=1 and Z=0 were matched in each propensity score levels. Conditional logistic regressions are widely used in "matched" case-control studies and for familial aggregation studies in genetics. Conceptually, this models fit separate intercepts at each matched propensity score levels. In the propensity score levels where all observations were Z=1 or Z=0 are dropped from the analysis.

Essentially there is no statistical procedure that can assess which of the above correction methods are more efficient in reducing the selectivity bias. As a result, we have applied all of these selected methods to correct selectivity bias, if any, and compare the results with individual level analysis, and infer the robustness of our findings.

Results

The differentials in contraceptive use, fertility level, unmet need, fertility preference, and maternal health care utilization by socio-economic status are shown in Table 1. Significant inequalities exist in all selected health outcomes. Maternal health care utilization shows the most pronounced inequality. Antenatal care was almost four times higher among the women in richest quintile, compared to the women in the poorest quintile (72.4% and 19.2%, respectively). The concentration index was highest for the delivery care; only 2% of women in the poorest group, compared to 35.8% women in the richest group, received institutional delivery care.

Individual level analyses show that family planning visitations significantly reduced inequality in modern contraceptive use (concentration index =0.095 (95% CI: 0.079-0.112) among individuals who were not visited by field workers, and CI=0.0099 (95% CI: -0.009 – 0.29) for the individuals who were visited by field workers (Table 2). Essentially, a statistically insignificant CI ($p>0.05$) suggests that there was no inequality in contraceptive use among women who were visited by family planning field workers. We also found that the concentration index for both female and male sterilization is "pro-poor" suggesting higher use of permanent methods in the poorer segments.

We have discussed earlier that it is possible that field workers selectively visited the women who had positive attitude towards contraceptive use and this may possibly introduce selectivity bias as family planning workers' visit to individuals may be endogenously determined. To avoid the problem of endogeneity, we examined the influence of family planning workers at the cluster level through an ecological measurement of outreach visitation (by the % of women visited by FP workers during last 6 months before the survey at each cluster). The results are shown in the last two columns of Table 2. Except for fertility level and unmet need, areas with higher levels of outreach activities show significant reductions in health inequalities in contraceptive use, and maternal health care utilization. The analysis comparing inequality in fertility and unmet need by higher coverage of visits by field health workers show limited impact (in the case of fertility, the concentration index reduced from –0.176 to –0.047; similarly, for unmet need, the concentration index reduced from –0.17 to –0.125, but neither significantly different).

Table 3. shows the log-binomial and Poisson model results based on ecological (cluster level) measurement of outreach visitation for the five selected health outcomes. All the standard error estimates are adjusted for clustering at geographical regions. Although outreach service availability significantly increased contraceptive use, antenatal care and institutional deliveries, and reduced fertility and unmet need, the negative values for the coefficients associated with the interaction terms suggest that the outreach service availability also significantly reduced the differentials in health care utilization by socioeconomic status for contraceptive use, antenatal care and delivery care, but not for fertility and unmet need. The most pronounced effect was observed for the contraceptive use.

Table 4 and 5 show the regression results based on propensity score weights and conditional logistic regression matched on propensity scores. These individual-based models were not fitted for the antenatal and delivery care outcomes because of the temporal ordering issues: outreach visits are based on recent period and these outcomes are like to temporally precede the visits.

The distributions of propensity scores between those who were visited and not-visited by outreach workers show the differences in selectivity by the known covariates are quite balanced (Fig. 2) . The regression results (Table 4 and 5) reconfirm the findings of the ecological based analyses that outreach visitations significantly reduced inequality in contraceptive use. In addition, these models that outreach visitation also reduced inequality in unmet need for contraception.

We further explored the differentials in contraceptive method choice in order to understand the limited role of outreach program activities in reducing inequality in fertility and unmet need. Although the overall contraceptive prevalence rate level was higher among women with higher socio-economic status, these women were more likely to practice the less effective methods, such as condoms and traditional methods (Table 6).

To gain insights into the possible mechanism of outreach visitation in reducing inequality, we have examined the pattern of visits by SES and education level of women. Fig. 3 suggests that visitations were more intense for the poorer and less educated women. These subjective targets of disadvantaged women may have played a significant role in reducing inequality.

Conclusion

It is often considered that since the 19th century one of the most consistent findings in epidemiological studies is the difference in mortality and morbidity by socioeconomic studies (Lynch and Kaplan, 2000). Although recently there is considerable debate surrounding the impact of socio-economic status on individual's health (Gravelle, H. 1983), several empirical studies show that income inequality significantly affect adult mortality, infant mortality and other health outcomes (Wolfson et al., 1999; Macinko, Shi and Starfield, 2004).

Recently a large number of studies have examined health inequality in developed countries. However, the major focus of these studies was to estimate the magnitude of health inequality at national level, rather than sub-group comparisons. In developed countries several studies have shown the effect of public programs in improving equity and concomitant reduction in health inequality. As an example, studies in the US show that enhancing primary care in states with high level of income inequality lead to lower all-cause mortality in such states (Shi et al., 2003; Lochner et al. 2001; Shi et al. 1999). This study is such an attempt to show the effect of family planning programs in the reduction of health care utilization inequality. During this early period of family planning program proliferation worldwide, the US also supported family planning programs through federal funds through Title X programs (Zabin, 1983), primarily to reduce unintended pregnancies, abortion and maternal deaths. Reaching vulnerable disadvantaged population remains the core targets of these health programs sponsored by federal funds.

Our study suggests that family planning program in Bangladesh significantly reduced inequality in contraceptive use, and to a lesser extent reduced inequality in unmet need and maternal health care utilization. The results, however, should be interpreted with caution. It may be inappropriate to solely credit family planning programs for the reduction of inequality in contraceptive use in Bangladesh based on the current analysis.

We have used two measures for family planning program: an individual level measurement (women visited by field workers in 6 months prior to the survey) and a community-level measurement (% of women visited by field workers in each cluster area). We discussed earlier, individual measurements may be affected by endogeneity as health workers may selectively visit women with positive attitude towards family planning or, conversely, more intensely visit poorly performing areas. A community level measurement with cluster level mean values of visitations without the index case to avoid endogeneity is not free from other contaminations: higher visitation areas may include other unobservable factors, such as urbanization, areas with better communication and health infrastructure, etc. However, a strong health care infrastructure is essential for family planning program. Hospitals, clinics, pharmacies and community health clinics serve as the potential delivery points for contraceptive methods and the service providers of such institutions serve to educate and motivate family planning clients for contraceptive practices (Potter, 1991). To robustly validate our findings, we have additionally used propensity scores to reduce selectivity bias. Our results strongly suggest that outreach family planning programs significantly reduced inequality in contraceptive use, and possibly to some extent in unmet need, ANC and delivery care.

With any modern health intervention it is likely that inequality in health care utilization will increase at the beginning as more affluent and educated individuals are more likely to initiate the use at the early phase. With the increase in use prevalence, the inequality is likely to start reducing as individuals from all sub-groups growingly participate in the program. Bangladesh has achieved remarkable success in family planning program. Within 25 years, contraceptive prevalence rate increased from 7.7% in 1975 to almost 50% in 199/2000, even without remarkable economic development. Studies show inequality in contraceptive prevalence rates is more pronounced in countries with lower prevalence levels (Gilespie and Radloff, 2003). Given that contraceptive prevalence is quite high in Bangladesh, overall inequality in contraceptive use is likely to be low. Nevertheless, we found that inequality in contraceptive use reduced significantly by family planning programs.

In Bangladesh, outreach workers have played the most pivotal role in improving contraceptive use and developing norm for smaller family size preference. These outreach workers not only provided family planning services, but also provided advice on overall health improvement, including maternal and child health care. Our study suggests that family planning outreach services reduced inequality in maternal health care as well.

We believe this study will stir a new interest in assessing the role of publicly funded health intervention programs on the reduction of inequality. About 150 million women still lack access to family planning information and services because of logistical, social, cultural, financial and behavior barriers. Our study results suggest that strong family planning programs can reach every segment of population, irrespective of their socioeconomic status, and reduce pervasive inequality that is still so prevalent.

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Fig.1: Concentration curve

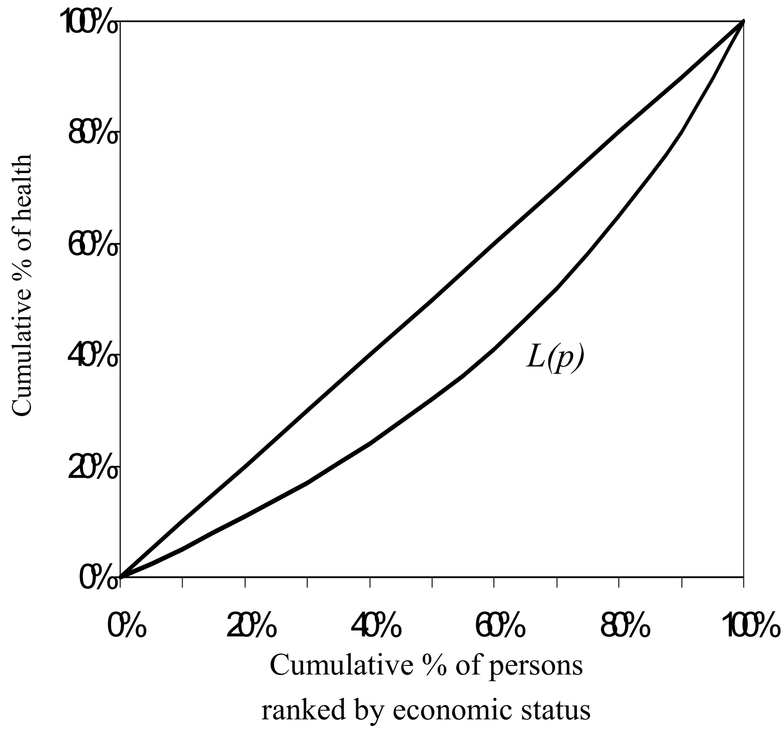

Fig. 2: Distribution of Propensity Scores by Family Planning Workers' Visit Status

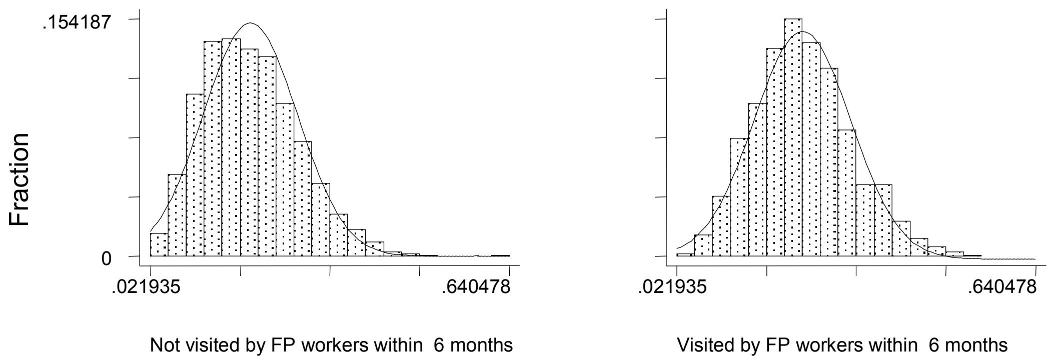

Fig. 3: Percent of Women Visited by Family Planning Workers by Socioeconomic Status and Educational Level

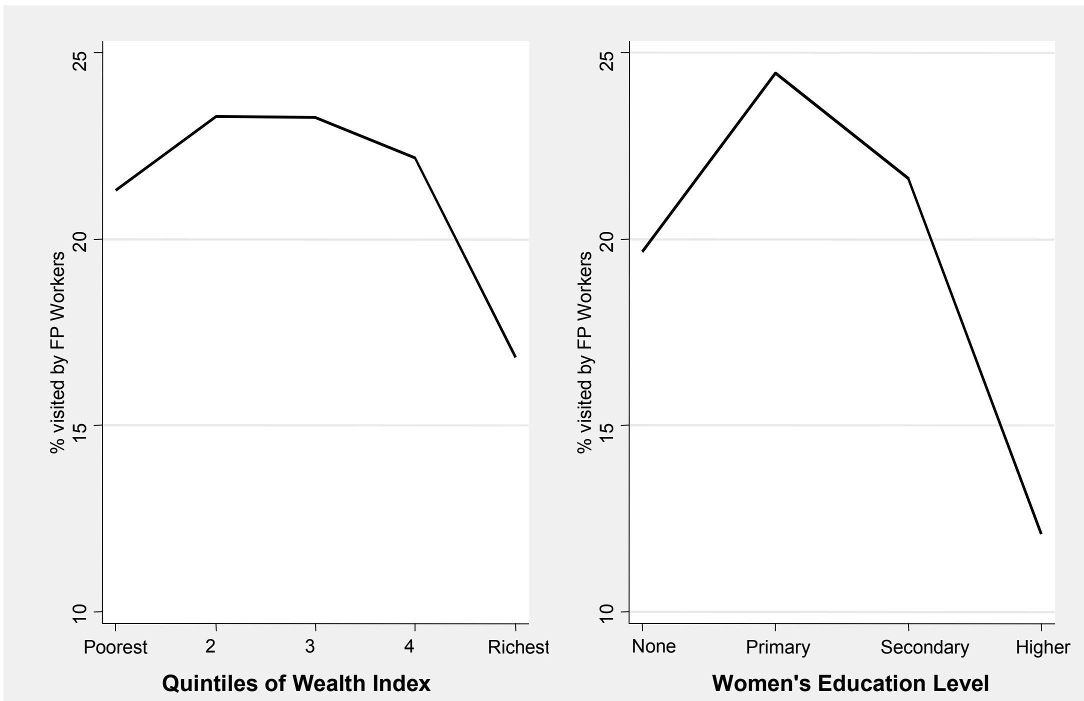

Table 1: Distribution of contraceptive use, fertility, and maternal health care in Bangladesh by socio-economic status

	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile	Concentration Index (95% CI)
Contraceptive use rate	32.6	39.3	40.7	41.1	46.5	0.066 (0.052-0.079)
Fertility level						
1 yr based[1]	180.5	150.4	157.0	121.6	103.2	-0.096(-.123; -0.069)
5 yr based[1]	169.1	145.8	132.3	114.1	98.7	-0.104 (-.115; -.092)
Unmet need	21.6	17.3	17.6	16.5	11.2	-.117 (-.142; -.091)
Antenatal care	19.2	23.1	30.0	41.6	72.4	.298 (.280-.317)
Delivery care	2.0	3.1	3.6	8.9	35.8	.604 (.549-.660)

1: General fertility rate (GFR): births per 1000 women of reproductive age

2. Among respondents with 2 or more surviving children

Table 2: Differentials in contraceptive use, fertility levels, contraceptive unmet need and maternal health care utilization, and inequality concentration index measures by service availability

	Individual level observation		Community level observation	
	Not visited by health workers[3]	Visited by health workers[3]	Low program area	High program area
Contraceptive use rate	**35.0**	**63.4**	**37.0**	**48.6**
1st quintile	25.9	61.4	22.4	42.5
2nd quintile	32.9	63.2	31.5	47.2
3rd quintile	34.9	62.1	35.0	48.9
4th quintile	35.1	64.3	41.0	49.8
5th quintile	43.0	65.9	44.1	55.3
Concentration index	0.095(0.079-0.112)	0.009 (-.009- .029)	.136 (.104-.167)	.047 (.022-.073)
Fertility level	**142.8**	**126.6**	**146.7**	**124.2**
1st quintile	185.5	158.9	215.7	138.7
2nd quintile	150.4	150.7	206.5	137.2
3rd quintile	162.5	136.7	157.1	130.7
4th quintile	126.9	101.4	127.1	111.7
5th quintile	105.8	88.9	102.2	99.3
Concentration index	-.095(-.125; -.065)	-.111 (-.177;-.044)	-.176 (-.234;-.116)	-.047 (.110; .016)
Unmet need	**17.6**	**12.1**	**18.4**	**12.7**
1st quintile	22.1	19.8	26.9	17.4
2nd quintile	19.2	10.8	23.7	13.7
3rd quintile	19.1	12.9	21.9	11.2
4th quintile	18.0	11.5	16.6	11.0
5th quintile	12.1	6.4	12.8	9.4
Concentration index	-.108 (.136; -.080)	-.184 (-.252;-.114)	-.170 (-.226;-.114)	-.125 (-.195;-.054)
Antenatal care	**36.3**	**39.3**	**41.9**	**41.1**
1st quintile	18.1	23.0	12.8	26.0
2nd quintile	21.8	27.1	21.6	35.4
3rd quintile	28.6	34.0	33.5	32.2
4th quintile	38.3	51.4	42.0	49.7
5th quintile	73.1	69.4	75.2	75.3
Concentration index	0.318 (.296-.340)	.242 (.204-.281)	0.354 (.322-.386)	.221 (.180-.261)
Delivery care	**11.0**	**10.0**	**15.1**	**10.6**
1st quintile	1.6	3.4	0.4	4.3
2nd quintile	2.2	5.9	3.1	6.6
3rd quintile	3.5	3.9	3.2	2.9
4th quintile	8.7	9.5	5.1	10.1
5th quintile	36.7	32.1	41.2	35.8
Concentration index	.642 (.579-.704)	.465(.348-.581)	0.666 (.574-.757)	.456(.333-.579)

1: General fertility rate (GFR): births per 1000 women of reproductive age

2. Among respondents with 2 or more surviving children

3. Visited by health workers during last 6 months prior to survey date.

Table 3: Log-binomial and Poisson regression model results showing reduction in health inequality by service availability based on cluster level service estimate.

	Contraceptive use	Fertility	Unmet need	Antenatal care	Institutional delivery care
Wealth index					
1st quintile	0.0	0.0	0.0	1.0	1.0
2nd quintile	0.29**	-0.13	-0.18	1.10**	2.07
3rd quintile	0.31**	-0.05	-0.09	1.58***	3.27
4th quintile	0.35**	-0.12	-0.14	1.75***	3.75*
5th quintile	0.45***	-0.09	-0.33**	2.31***	12.4***
Service availability	0.07***	-0.33**	-0.04**	1.15*	1.49*
Interaction terms:					
1st quintile SA*	0.0	0.0	0.0	1.0	1.0
*2nd quintile*SA*	-0.03*	0.07	0.0	0.98	0.86
*3rd quintile*SA*	-0.03*	0.10	-0.02	0.88	0.70
*4th quintile*SA*	-0.04**	-0.12	-0.01	0.91	0.86
*5th quintile*SA*	-0.05***	0.06	-0.02	0.89*	0.68*

Adjusted for age, number of surviving children, children died, education, education of husband, religion, participation in women's development programs, exposure to mass media, women's status and urban/rural residence.
*** p<.01; ** p<0.05; * p<0.1

Table 4. Log-binomial and Poisson regression model results showing reduction in health inequality by service availability based on individual level propensity scores as probability weights.

	Contraceptive use	Fertility	Unmet need
Wealth index			
1st quintile	0.0	0.0	0.0
2nd quintile	0.15**	-0.11	-0.14
3rd quintile	0.22**	-0.01	-0.18**
4th quintile	0.20**	-0.08	-0.18*
5th quintile	0.32***	-0.10	-0.41***
Service availability	0.65***	-0.27*	-0.34***
Interaction terms:			
1st quintile SA*	0.0	0.0	0.0
*2nd quintile*SA*	-0.13*	-0.03	-0.37*
*3rd quintile*SA*	-0.28***	0.04	-0.18
*4th quintile*SA*	-0.24***	-0.21	-0.24
*5th quintile*SA*	-0.35***	0.01	-0.59**

Adjusted for age, number of surviving children, children died, education, education of husband, religion, participation in women's development programs, exposure to mass media, women's status and urban/rural residence.
*** p<.01; ** p<0.05; * p<0.1

Table 5. Conditional logistic regression matched on propensity scores model results showing reduction in health inequality by service availability

	Contraceptive use	Fertility	Unmet need
Wealth index			
1st quintile	0.0	0.0	0.0
2nd quintile	0.27**	-0.19*	-0.17
3rd quintile	0.37**	-0.08	-0.21*
4th quintile	0.29**	-0.17	-0.19*
5th quintile	0.49***	-0.13	-0.47***
Service availability	1.31***	-0.45**	-0.39**
Interaction terms:			
1st quintile SA*	0.0	0.0	0.0
*2nd quintile*SA*	-0.23	0.09	-0.45*
*3rd quintile*SA*	-0.45***	0.13	-0.24
*4th quintile*SA*	-0.32*	-0.14	-0.28
*5th quintile*SA*	-0.58***	0.09	-0.51*

Adjusted for age, number of surviving children, children died, education, education of husband, religion, participation in women's development programs, exposure to mass media, women's status and urban/rural residence.
*** p<.01; ** p<0.05; * p<0.1

Table 6. Differentials in contraceptive method choice by socio-economic status

	Lowest economic status (Lowest quintile)	Highest Socioeconomic Status (Highest quintile)
No contraceptive use	60.0	41.5
Pill	15.8	23.7
IUD	0.73	1.9
Injectables	7.3	4.4
Condom	1.2	11.0
Male sterilization	0.7	0.2
Female sterilization	6.9	5.5
Traditional methods	6.6	11.8