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Evaluating the Impact of Full Coverage Health Communication Programs Using Non-experimental Data: An Analysis Using Bivariate Probit and Matching Estimators in Tanzania and Nepal

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Abstract

Evaluations of national full-coverage health behavior change communication campaigns are frequently plagued by reliance on measures of self-reported exposure to media messages from the same population-based surveys in which data for behavior change are collected. Measures of self-reported exposure to media messages complicate evaluations since they are likely to be non-random, reflecting a variety of measured characteristics (e.g. access to media, attitudes, education) and unmeasured characteristics of respondents (e.g. motivations, health conscientiousness, or supply-side variables). Several recent studies have noted that improper heed being paid to non-random exposure can lead to estimates of the effectiveness of communication efforts that are substantially biased. In order to address non-random reporting of exposure, multivariate evaluation techniques with suitable controls are often used. This study employs and compares the performance of two quantitative methods to address and to correct for the problems of non-random assignment of individuals to treatment (exposed to the communication program) and control groups (non-exposed): (1) maximum likelihood simultaneous equations methods, in particular bivariate probit, that assume a joint normal distribution for the correlation in unobservables affecting discrete measures of exposure and outcomes; (2) matching estimators which compare differences in behavior across groups with similar observed characteristics or likelihoods of exposure. These methods are used to evaluate the impact of family planning health communication campaigns on current use of modern family planning, focusing on *Zinduka!* and more general measures of family planning message exposure in Tanzania, and on *Ghati Heri Haad Nilaun* in Nepal. Data come from the 1999 Tanzania Reproductive and Child Health Survey and the 2001 Nepal Demographic and Health Survey. The results indicate that analyses using estimation methods based on assumptions of exogeneity of mass media exposure in family planning use equations can seriously misrepresent the effects of mass media.

Evaluating the Impact of Full Coverage Health Communication Programs Using Non-Experimental Data: An Analysis Using Bivariate Probit and Matching Estimators in Tanzania and Nepal

Background

Behavior change communication campaigns use television, radio, and other media to transmit important information about health issues, to demonstrate norms and ideals regarding behaviors, and to promote beneficial social change. Increasingly, program officers and countries are called upon to demonstrate the effectiveness of their campaigns in achieving some objective, for example, reduced smoking, increased use of family planning, or improved HIV/AIDS preventive behaviors. Evaluations of such campaigns use a variety of methods and research designs to measure effectiveness: regression discontinuity designs, pre- and post-evaluation designs with statistical controls for exposure, post-only cross sectional surveys, longitudinal (panel) surveys or, in rare cases, randomized control group designs (Bertrand and Kincaid 1996, Piotrow et al 1997. MEASURE *Evaluation* and Population Communication Services Project 2002, Moffitt 1991, Guilkey, Hutchinson and Lance 2005).

While the chosen methods in any evaluation are often dictated by research budgets or characteristics of the communication program itself, health communication program evaluations generally rely upon comparisons of outcomes between those who have heard, seen or read a specific media message and those who have not. Such comparisons are relatively straightforward if randomized control group (RCG) designs are used, that is, when selection of who is exposed to media messages is random and the selection process is uncorrelated with outcomes of interest. The average outcome for those exposed is simply compared to the average outcome for those unexposed. Since exposed and unexposed individuals are expected to be statistically equivalent in all relevant characteristics and any other differences are assumed to reflect chance, differences in average outcomes can be attributed to the effects of the program. Unfortunately for evaluators, however, the nature of media message delivery is generally such that it is seldom possible to exclude individuals using randomization (Kincaid and Do 2003, Bertrand, Kincaid and Babalola 2004).

Researchers are occasionally presented with the possibility of using "natural experiments" that roughly approximate an RCG design. An example might be a media campaign concerning family planning that airs in one region of a country and not another, as was the case with the *Twende Na Wakati* radio drama program in Tanzania (Vaughan et al 2000). If the decision to broadcast such messages in a specific region is unrelated to factors that affect family planning use – a logical stretch if resource allocation decisions are rationale and based on sound data – then the effectiveness of the media program could be calculated as the difference in the average outcomes across the two regions, assuming statistically equivalence on other factors affecting family planning use, for example attitudes towards family planning, wealth, access to services. In other words, if it could be assumed that individuals in the two regions were identical on average in all respects except exposure to the family planning media messages, then any difference in average outcomes would be attributable to the media messages. However, even local media campaigns are rarely truly random and the processes underlying decisions to implement such campaigns are seldom known, meaning that simple comparisons of average outcomes may be contaminated by other factors (Angeles, Guilkey and Mroz 1999, Pitt, Rosenzweig and Gibbons 1993, Gertler and Molyneaux 1994).

However, the increasing use of communication strategies that are national in scope generally obviates the use of RCG designs or precludes the possibility of having natural experiments. Further, many studies of the effectiveness of behavior change communication programs rely upon self-reported measures of exposure, such as whether or not survey respondents in large nationally representative population surveys report having heard a specific family planning message within a defined time period. While such data still permit comparisons between those reporting exposure to a media message and those who do not, the assumptions of statistical equivalence require greater scrutiny. At the very least, exposed individuals in developing countries are likely to differ in many measurable ways, such as whether or not they are literate, have access to common media sources (television, radio, internet, newspapers), or live within the broadcast area of such messages. They may also differ in ways that are not easily measured by researchers, such as being more motivated to access health information, having greater health competence, living in areas where cultural norms are more favorable towards lower fertility and greater family planning use or (in the absence of information on health services) having greater access to family planning services.

When exposure to mass media is determined by measurable characteristics of individuals (such as in which part of the country they live), or by a process that is independent of the outcomes of interest (such as use of contraception), researchers have a wide variety of evaluation tools at their disposal for determining the impact of the media activities. Many of these tools have been described and applied extensively in the economics and statistics, specifically in the evaluation of job training programs (LaLonde 1986, Moffitt 1991, Heckman et al 1996, Heckman, Ichimura and Todd 1997, Heckman et al 1998, Smith and Todd 2004, Imbens 2004, Heckman and Navarro-Lozano 2004).

A common method for evaluating the effects of health communication media is to estimate a single-equation econometric model with a health outcome regressed on a set of covariates, including a measure of exposure to a health communication program. Program impact is measured as the partial effect from the regression coefficient for the exposure variable, controlling for other observable characteristics of individuals. This partial effect is often measured in terms of the odds of experiencing the outcome relative to not experiencing the outcome (Van Rossem and Meekers 2000, Agha 2002, Agha and Van Rossem 2002, Bessinger, Katende and Gupta 2003, Gupta, Katende, and Bessinger 2003, Kincaid et al 1993, Kincaid et al 1996).

An alternative to econometric models has recently been introduced to the literature on the evaluation of communication programs by Kincaid and Do (2003), who used matching estimators that compare outcomes for exposed and unexposed individuals with similar observed characteristics or similar likelihoods of being exposed. Matching estimators have several strong features, specifically that they allow for heterogeneous treatment effects and that they do not make parametric assumptions about the distribution of the conditional density function (Conniffe, Gash and O'Connell 2000).

In both single-equation econometric models and matching methods, however, it is assumed either that exposure to media messages is random and independent of health outcomes or, if not, that health outcomes can be conditioned solely on exposure to mass media and observed characteristics of individuals. These are very strong assumptions under many circumstances, particularly when measures of exposure are determined by individuals' recall of mass media messages, which may reflect underlying unmeasurable factors that also influence health outcomes. For example, individuals who are more motivated to control their fertility, an effect that may not be measured by researchers, may be more likely both to notice family planning media messages and to make the efforts to access available family planning services. In this case, exposure to mass media is considered to be endogenous; the unobservable level of motivation affects both recall and contraceptive use, biasing estimates of the effect of exposure to mass media on contraceptive use in both matching and single equation econometric estimations (Imbens 2004, Belmont Report 2003; Bertrand, Kincaid and Babalola 2004, Moffitt 1991, Guilkey, Hutchinson and Lance 2005).

In this paper, we examine the performance of two methods for evaluating the impact of the mass media health communication efforts based on observational data: (1) maximum likelihood simultaneous equations methods, such as bivariate probit, that assume a joint normal distribution for the correlation in unobservables affecting discrete measures of exposure and outcomes; and (2) matching estimators which compare outcomes across groups with similar observed characteristics or similar likelihoods of exposure based on those observed characteristics. These two classes of estimators are chosen largely for their accessibility for program evaluators with readily available statistical software packages like Stata 9.0. More complex econometric methods are also available for addressing endogenous binary regressors, many of which do not require stringent parametric assumptions, but these are not examined here.

We focus here on the effects of mass media on contraceptive use primarily because of the abundance of data sets, particularly Demographic and Health Surveys (DHS), which contain information on both exposure to family planning media messages and on contraceptive use. For our analysis, we utilize data from two DHS's – the 1999 Tanzania Reproductive and Child Health Survey and the 2001 Nepal Demographic and health Survey.

We parallel the work of Kincaid and Do (2003) in their effort to measure the effectiveness of a family planning media effort in the Philippines using both instrumental variables and propensity score matching. We differ in this case in two important ways. First, we treat exposure to family planning media messages as binary – a person is either exposed to the media messages or not. This generally limits the use of standard instrumental variables approaches for addressing endogenous regressors, such as two-stage least squares, which will provide parameter estimates that are inconsistent when the endogenous variable is binary. This also limits measuring the effects of different levels of exposure, though multiple binary exposure measures – representing exposure from different media (TV, radio, newspaper) could be possible under certain conditions in a multiple simultaneous equation model. Finally, we do not include prior information, such as lagged values of the dependent variable, in our models.

It should be clear that the aim is not to prove the superiority of one method over another; the two methods are most appropriate, that is they provide unbiased, consistent, and efficient estimates, under different circumstances depending upon the validity of exogeneity assumptions. Rather, we attempt to provide examples of how the two methods perform under common conditions when non-experimental cross sectional survey data are used to gauge the effectiveness of health communication activities. Further, we raise several issues likely to be faced by evaluators, such as the need for tests for endogeneity and the importance of suitable exclusion restrictions.

Methodology

Many of the methods described here originate from the work of Rosenbaum and Rubin (1983) and Rubin (1974) and others regarding the estimation of average treatment effects, which have been ably summarized by Wooldridge (2002) and described in greater detail by various researchers (Heckman, Ichimura and Todd 1997, Heckman and Robb 1985). This literature can be applied here by considering exposure to mass media as analogous to a treatment effect.

We start by defining outcome Y_i for individual i from a sample of i=1…N individuals and critically assume that these N individuals are drawn at random from an underlying population. We assume that Y_i is binary, more specifically that Y_i represents whether or not a women uses modern family planning. We further define a woman's outcomes as Y_{1i} if she is exposed to the family planning mass media and as Y_{0i} if she is not. The appropriate measure of the effect of mass media for a specific woman is the difference in outcomes with and without the treatment, i.e. $Y_{1i} - Y_{0i}$. Calculation of this value, however, is inherently impossible, as a woman can only be observed in one of the states - exposed or not – but not both. That is, the calculation of the effect of the communication program is limited by absence of information about the counterfactual situation for any woman.

Under certain conditions regarding the independence of exposure to mass media and the outcomes, different estimates of the treatment effect of a communication program are possible. The treatment literature defines several types of measures of the effect of treatment, or exposure, on the outcome. Most prominent is the average treatment effect (ATE) for an individual drawn at random from the population:

$$(1) \qquad ATE \equiv E(Y_{1i} - Y_{0i})$$

Alternatively, one can calculate the average treatment effect on the treated (ATT), which may serve, under some evaluations, as a more relevant sub-population for analysis:

$$(2) \qquad ATT \equiv E(Y_{1i} - Y_{0i} | D_i = 1)$$

where $D_i=1$ indicates that individual i has been exposed to the family planning message in contrast to not being exposed ($D_i=0$). When exposure to the family planning message D_i is statistically independent of the outcomes Y_{0i} and Y_{1i}, the two effects are identical, that is,

$$(3) \qquad E(Y_{1i} - Y_{0i} | D_i = 1) = E(Y_{1i} - Y_{0i})$$

Under such conditions, randomization ensures that the above estimator is unbiased, consistent and asymptotically normal (Wooldridge 2002). If treatment is not completely random but instead is a function of observable characteristics of individuals, i.e. individuals with certain characteristics tend to self-select themselves into the treatment and non-treatment groups, (1) and (2) can be extended by conditioning on the observable characteristics X_i such that:

$$(4) \qquad ATE \equiv E(Y_{1i} - Y_{0i} | X_i), \text{ and}$$

$$(5) \qquad ATT \equiv E(Y_{1i} - Y_{0i} | D_i = 1, X_i).$$

In this latter framework, a women's use of family planning is determined by a set of observable characteristics X_i that may include such important explanatory variables as levels of education, age at marriage, socioeconomic status, occupation, or, depending upon data availability, characteristics of the health service supply environment.

An essential condition that allows for identification of treatment effects is that of ignorability of treatment conditional upon observed explanatory variables, often generalized to the assumption of conditional mean independence of treatment and outcomes, namely:

$$(6) \qquad E(Y_{1i} \mid D_i, X_i) = E(Y_{1i} \mid X_i) \text{ and } E(Y_{0i} \mid D_i, X_i) = E(Y_{0i} \mid X_i)$$

Under this latter assumption, both matching methods and single-equation regression-based approaches allow for calculation of average treatment effects once observed covariates are conditioned upon or partialled out.

Matching estimators

Matching estimators are based on the assumption that available data on exposed and unexposed individuals are sufficiently all-encompassing that the missing counterfactual information for exposed individuals can be gleaned from a sample of unexposed individuals with similar observed characteristics. The difficulty with matching estimators is in determining when matches for exposed and unexposed individuals are "close enough." Many different matching methods have been proposed, including one-to-one matching (nearest neighbor, caliper matching, with or without replacement), k-nearest neighbor matching, radius matching, kernel matching, local linear regression matching, spline matching and Mahalanobis matching.

One subset of matching estimators is that based on propensity scores, originating in the work of Rosenbaum and Rubin (1983). The method of propensity scores involves calculating the prior probability of having heard, seen or read a family planning message conditional upon observed characteristics of individuals, namely:

$$(7) \qquad p(X_i) \equiv P(D_i=1 \mid X_i)$$

where $p(X_i)$ is defined in the matching literature as the propensity score. Again, assuming conditional mean independence of treatment and outcomes, the expected difference in the outcomes is given by:

(8) $$E[Y_{1i} \mid D_i=1, p(X_i)] - E[Y_{0i} \mid D_i=0, p(X_i)] = E[Y_{1i}\, Y_{0i} \mid p(X_i)]$$

The method of matching that we use here is based on stratification of propensity scores into blocks of exposed and unexposed individuals. Estimation of the average treatment effect based on stratification involves first calculating the propensity score using a standard probit or logit model (Becker and Ichino 2002, Kincaid and Do 2003). Using the predicted propensity score for each individual, the sample is then divided into equally-spaced intervals of the propensity score. A minimum of 5 blocks has been shown to be adequate. Within each block, the mean propensity scores for exposed and unexposed individuals are compared and tested to see if the are identical. If they are not, the interval is split in half and then the test is re-done. Once equality of propensity scores within blocks has been achieved, characteristics of individuals within blocks are then compared to see if they are identical on average. If this balance is achieved within blocks, the average treatment effect is calculated from the weighted average of the difference in the outcome in each block between those exposed and those not exposed.

The principal advantage of the propensity score is that it makes no assumptions about the distribution of the outcomes for family planning. As emphasized by Heckman et al (1998),

> The advantage of using the propensity score is simplicity in estimation. When we use the method of matching based on propensity scores, we can estimate treatment effects in two stages. First we build a model that describes the programme participation decision. Then we construct a model that describes outcomes. In this regard, matching mimics the features of the conventional econometric approach to selection bias.

On the other hand, propensity score methods have clear limitations, as noted by Rubin (1997):

> It is important to keep in mind that even propensity score methods can only adjust for observed confounding covariates and not for unobserved ones. This is always a limitation of nonrandomized studies compared with randomized studies, where the randomization tends to balance the distribution of all covariates, observed and unobserved.

In the analysis that follows, we estimate the average treatment effect on the use of family planning from exposure to mass media using the *pscore* and *atts* commands in Stata 9.0.

Simultaneous Equations Models

An alternative to matching estimators are econometric models in which exposure to mass media is included explicitly as an explanatory variable in an equation for contraceptive use, as in (9). If exposure D_i is not correlated with the unobservable term, ε_i, estimation of the treatment/exposure effects can proceed directly using a single equation model, such as probit, usually estimated by maximum likelihood methods. If, on the other hand, D_i is correlated with the unobservable term, instrumental variables methods can be used to remove the correlation or simultaneous equations methods can be used to model the correlation of the unobservables across equations (Heckman 1978, Ashford and Sowden 1970).

In the simple case with independence of exposure and unobservable effects, we can model our family planning outcome Y_i as a probit with explanatory variables X_i and the mass media exposure variable D_i:

$$(9) \qquad Y_i^* = X_{i1} \cdot \beta_1 + D_i \cdot \delta + \varepsilon_{i1}$$

Using a latent variable characterization in which Y_i^* represents an underlying propensity to use modern contraception, a woman is observed to use modern contraception (Y_i=1) when Y_i^* exceeds an arbitrary threshold equal to 0 and is observed not to use modern contraception (Y_i=0) when Y_i^* does not exceed the threshold, specifically:

$$(10) \qquad Y_i = \begin{cases} 1 & if \quad Y_i^* > 0 \\ 0 & if \quad Y_i^* \le 0 \end{cases}$$

In the simple case, the error term in (9) is assumed to be independent and identically distributed with $E(\varepsilon_{i1})=0$ and $Var(\varepsilon_{i1})=\sigma_{\varepsilon 1}$. Because we are specifying a probit model, ε_{i1} is assumed to have a normal distribution.

Under this framework, the estimate of the effect of mass media exposure, controlling for other observed characteristics X_{i1}, on the outcome Y_i is given by the coefficient δ. Under classical regression assumptions, specifically the use of an independent and identically distributed random sample of individuals and $Cov(D_i, \varepsilon_{i1}) = 0$, that is, exposure to mass media messages is uncorrelated with unobservable factors that also affect contraceptive use, δ will be an unbiased and consistent estimate of the partial effect of mass media exposure on contraceptive use.

The latter assumption of independence of D_i and ε_{i1} is equivalent to the ignorability assumption of the Rosenbaum and Rubin (1983) matching estimators, and there are numerous scenarios under which this assumption might not hold. For example, governments might target mass media messages to areas with underlying (unmeasured) differences in factors affecting the uptake of family planning (local attitudes, norms, acceptability of family planning), thereby introducing cluster-level heterogeneity. Alternatively, the recall of mass media messages related to family planning could be associated with (unmeasured) individual-level factors affecting the uptake of family planning (e.g. underlying motivations, current or past-use of family planning, perceptions of community norms, etc.). The potential targeting of family planning programs has been noted by several researchers (Angeles, Guilkey and Mroz 1999, Pitt, Rosenzweig and Gibbons 1993, Gertler and Molyneaux 1994). The result is a form of sample selection bias - the sample of individuals who report having heard or seen a communication message is different from those who do not report having heard or seen a communication message in unmeasurable ways that are also correlated with family planning use.

When $Cov(D_i, \varepsilon_{i1}) \neq 0$, i.e. when exposure to mass media messages is endogenous, naïve single-equation regression models, such or ordinary least squares or probit will produce biased and inconsistent parameter estimates, reflecting the combined effect of exposure and motivation or fertility norms but attributing the net effect to exposure alone.

One strategy for addressing the endogeneity of mass media message recall in (9) is to model explicitly an equation for exposure to mass media and then to estimate this equation jointly with the family planning equation, allowing for correlation in the unobservable factors across the two equations. In this formulation, recall of exposure to mass media is determined by a set of observed covariates X_{i2}. It is assumed that, while there may be partial overlap of X_{i1} and X_{i2}, X_{i2} will include at least one explanatory variable not in $X_{i1,}$ i.e. at least one covariate that uniquely affects media exposure but not family planning use, though this assumption is not essential:

(11) $$D_i = X_{i2} \cdot \beta_2 + \varepsilon_{i2}$$

As with the family planning outcome, we model D_i as continuous underlying latent variable for the propensity to recall family planning messages, with observed discrete realizations given by D_i=1 (recall) if D_i^* exceeds an arbitrary threshold and by D_i=0 otherwise:

(12) $$D_i = \begin{cases} 1 & if \quad D_i^* > 0 \\ 0 & if \quad D_i^* \le 0 \end{cases}$$

We assume $E(\varepsilon_{i2})=0$ and $Var(\varepsilon_{i2})=\sigma_{\varepsilon 2.}$ Additionally, we assume that the error terms ε_{i1} in (9) and ε_{i2} in (11) are correlated and follow a joint normal distribution with $corr(\varepsilon_{i1}, \varepsilon_{i2}) = \rho$.

Estimation of the simultaneous equation model of (9) and (11) is undertaken based on maximizing the likelihood function, constructed as the product of each individual's joint probability of being exposed to the family planning message and using contraception. The likelihood function incorporates four possible outcomes: (1) exposure to mass media and use of family planning (D_i=1 and Y_i=1), (2) use of family planning but no exposure (Y_i=1 and D_i=0), (3) exposure to mass media but no use of family planning (D_i=1 and Y_i=0), and (4) no exposure and no use of family planning (D_i=0 and Y_i=0).

(13) $$\prod_{i=1}^{N} \left[\Pr(Y_i = 1 \quad \& \quad D_i = 1)\right]^{Y_i \cdot D_i} \left[\Pr(Y_i = 1 \quad \& \quad D_i = 0)\right]^{Y_i \cdot (1-D_i)}$$

$$\left[\Pr(Y_i = 0 \quad \& \quad D_i = 1)\right]^{(1-Y_i)\cdot D_i} \left[\Pr(Y_i = 0 \quad \& \quad D_i = 0)\right]^{(1-Y_i)\cdot(1-D_i)}$$

Using the assumption of joint normality in the distribution of ε_{i1} and ε_{i2}, the first term in (13) is given by:

(14) $$\Pr(Y_i = 1 \quad \& \quad D_i = 1) = \Pr(\varepsilon_{i1} > -X_{i1}\beta_1 \quad \& \quad \varepsilon_{i2} > -X_{i2}\beta_2)$$

$$= \int_{-X_{i1}\beta_1}^{\infty} \int_{-X_{i2}\beta_2}^{\infty} \phi(\varepsilon_{i1}, \varepsilon_{i2}, \rho) \partial\varepsilon_{i1} \partial\varepsilon_{i2} = \Phi(X_{i1}\beta_1, X_{i2}\beta_2, \rho)$$

where $\Phi(\cdot)$ is the bivariate normal cumulative distribution function, and $\phi(\cdot)$ is the bivariate normal probability density function. The other probabilities in the likelihood function are constructed similarly making use of both the above bivariate normal c.d.f. and the appropriate univariate normal c.d.f.

A straightforward test of endogeneity in the bivariate probit model is H_0: $\rho=0$. In the absence of a value of ρ that is statistically different from 0, estimation of (9) can proceed using single-equation probit.

In the analysis below, we use two estimators in Stata 9.0 for the bivariate probit model: maximum likelihood using the *biprobit* command and simulated maximum likelihood using the Geweke-Hajivassiliou-Keane (GHK) simulator for evaluation of the bivariate normal integrals with the *mvprobit* command. To the best of our knowledge, the only example of an evaluation of a health communication campaign that uses a bivariate probit model is Hutchinson, Lance, Guilkey, Shahjahan and Haque (2005).

Results

To provide a broad view of propensity score matching and bivariate probit estimators in the context of the evaluation of health communication programs, we present results reflecting common analytical situations, namely when exposure to mass media is exogenous and when it is endogenous. Data from two countries are used in the analysis, specifically Tanzania and Nepal. All analyses use as the dependent variable a binary outcome indicating whether or not a woman is currently using modern family planning.

Case #1 Assessment of treatment effect when exposure is exogenous: Zinduka! in Tanzania

Data for Case #1 come from the 1999 Tanzania Reproductive and Child Health Survey (TRCHS-99). The TRCHS-99 was carried out with the purpose of collecting national level data on reproductive, maternal and child health issues as well as data on the availability of health services within communities. Implemented by the Tanzanian National Bureau of Statistics and the Reproductive and Child Health Section of the Ministry of Health (with technical assistance from Macro International Inc.), the survey followed a three-stage sample design and consisted of a household component and a health facility component (National

Bureau of Statistics and Macro International Inc. 2000). Community level information (at the cluster level) was collected in 1999 by the MEASURE Evaluation Project at the Carolina Population Center (Ukwuani et al. 2003).

The key explanatory variable of interest for Case #1 in Tanzania was a binary variable capturing whether respondents recalled listening to *Zinduka!* within the past six months. *Zinduka!*—a 52 episode radio serial drama— was a component of a larger program implemented by the Health Education Division of the Ministry of Health of Tanzania and the Johns Hopkins University/Population Communication Services. The radio soap opera was designed to educate listeners about the health benefits of modern contraception. Messages woven into the story lines conveyed the importance of family planning and promoted positive attitudes toward women (The Communication Initiative 2005). Along with socio-demographic control variables, four community variables that measured family planning availability (distance to nearest health facility in km, whether the village is visited by a health assistant or a community health worker, and whether the community has a community based distributor) and community attitudes toward family planning (whether the local government strongly encourages family planning) were included in the model.

Table 1 presents the weighted univariate distributions for key variables in the model. One third (33.2%) of women reported listening to *Zinduka!* in the 6 months preceding the survey. However, contraceptive use was quite low—overall only 16.7% of women reported currently using a modern contraceptive method at the time of the survey.

We begin the evaluation of the effect of *Zinduka!* listenership on contraceptive method use by estimating several equations: simple probit models for exposure to *Zinduka!* and use of modern contraception and then the two bivariate probit models using maximum likelihood and simulated maximum likelihood. The simple probit models are used to get an estimate of the effect of *Zinduka!* on contraceptive use assuming exogeneity, as well as to test the validity of our exclusion restrictions in the model, namely whether or not identification can be achieved by including variables in the model that significantly affect exposure to *Zinduka!* but not use of modern contraception. As noted by Schultz (2004), the identification of suitable exclusion restrictions in simultaneous equation models in health is a perpetually vexing problem. The models were run using three instrumental variables (listens to radio weekly, watches television weekly, and whether or not the village has an all year road). In all cases, using an F test, the instrumental variables were jointly significant in the *Zinduka!* exposure equation but not in the contraceptive use equation. Further, in both bivariate probit models, we failed to reject the null hypothesis $H_0 : \rho = 0$ of exogeneity of *Zinduka!* listenership in the modern contraceptive use equation. Endogeneity of exposure to the radio program was thus ruled out.

Results for the probit and bivariate probit models are presented in Table 2. Using all three methods of estimation, exposure to *Zinduka!* was significantly associated with current contraceptive use. Marital status, belonging to the second highest or highest asset quintile, number of years of education, and belonging to an older age category were all consistently, positively and significantly associated with contraceptive use. Figure 1 shows the predicted probabilities of contraceptive use by each method of estimation. Simulating full exposure increased current modern contraceptive use to 22.6% by the probit estimation model, to 26.5% by the *biprobit* maximum likelihood estimation, and to 25.3% by the *mvprobit* simulated maximum likelihood estimation. The absence of the program reduced the current use of modern contraceptives to 13.7%, 11.6% and 12.1% for the simple probit, *biprobit*, and *mvprobit* respectively. Because we failed to reject the exogeneity of *Zinduka!,* the preferred (and most efficient) estimation method was the simple probit model.

Table 3 presents the results of the propensity score analysis of current use of modern contraception on exposure the *Zinduka!* radio program using the stratification method. The propensity score calculation yielded a total of 8 blocks, though no women were found in the lowest block. The difference in the percentage of users between those exposed and those unexposed for each block was weighted by the number of exposed individuals in each block, yielding an overall weighted average treatment effect of 10.5% when summing across blocks. The treatment effect estimated by propensity score analysis was similar to that obtained by the preferred maximum likelihood estimation method, simple probit, which yielded a treatment effect of 9.0%. The SEM models yielded larger exposure effects of 14.9% and 13.2% for *biprobit* and *mvprobit* respectively (Figure 2).

Case #2 *Assessment of treatment effect when exposure is exogenous: Exposure to Ghati Heri Haad Nilaun in Nepal*

Data for Case #2 of this analysis come from the 2001 Nepal Demographic and Health Survey (NDHS). The NDHS was carried out in order to collect national level data on reproductive, maternal and child health issues, as well as on the utilization of maternal and child health services. The survey was implemented by a local research organization (New ERA) under the auspices of the Family Health Division of the Department of Health Services (with technical assistance from Macro International Inc.). The survey followed a two-stage, stratified sample design to select a nationally representative sample of ever-married women (Ministry of Health [Nepal], New ERA, and ORC Macro, 2002).

The key explanatory variable of interest for Case #2 was a dichotomous variable capturing whether respondents recalled listening to *Ghati Heri Haad Nilaun* within the past few months. *Ghati Heri Haad Nilaun* was a component of the Radio Communication Project (RCP) which was devised by Ministry of Health, the National Health Education, Information, and Communication Center (NHEICC), and the Population Communication Services of Johns Hopkins University to increase the demand for family planning products and improve the quality of family planning service delivery. The radio soap opera was designed to promote the concept of a "well planned family" by improving the public perceptions of service providers, promoting community involvement and encouraging interpersonal communication (Storey and Boulay 2000). Along with socio-demographic control variables, the model also included a set of variables describing the education achievement of the respondent's husband.

Table 4 presents the weighted univariate distributions for key variables in the model. Close to one-third (34.1%) of women reported listening to *Ghati Heri Haad Nilaun* in the past few months. One-third of women (34.5%) reported currently using a contraceptive method at the time of the survey. A cross-tabulation of these variables shows that a higher percentage (42.5%) of women who had listened to *Ghati Heri Haad Nilaun* were currently using modern contraception as compared to women not listening to the program (31.2%). To rule out the potential endogeneity of exposure to *Ghati Heri Haad Nilaun* on the outcome of interest, SEM models were run using a single instrumental variable (listens to radio weekly). As can be seen in Table 5, the instrumental variable was significant in the *Ghati Heri Haad Nilaun* equation but not significant in the outcome equation. As in Case#1, both SEM methods (*biprobit* and *mvprobit*) failed to reject the null of exogeneity of *Ghati Heri Haad Nilaun* listenership in the modern contraceptive use equation, thus endogeneity of exposure to the radio program was ruled out.

Results for both estimation methods, as well as the simple probit estimation method, are presented in Table 5. Using all three methods of estimation, exposure to *Ghati Heri Haad Nilaun* was significantly associated with current contraceptive use. Belonging to an older age category, belonging to a higher asset quintile, having been visited by a FP worker, being employed, having a husband of with formal education and watching television every week were all consistently, positively and significantly associated with contraceptive use in all three estimation methods. Number of living children was also significantly associated with modern contraceptive use. Being of Muslim or "other religion" (which includes Christianity) and living in a rural area were consistently, negatively and significantly associated with the outcome in all three estimation methods.

Figure 3 shows the predicted probabilities of contraceptive use by each method of estimation. Exposure to *Ghati Heri Haad Nilaun* increased current modern contraceptive use and this increase was observed using all three estimation methods. As seen in Figure 3, simulating full exposure increases current modern contraceptive use to 39.2% by the probit estimation model, to 40.8% by the *biprobit* maximum likelihood estimation, and to 40.7% by the *mvprobit* simulated maximum likelihood estimation. The absence of the program reduced the current use of modern contraceptives to 33.0%, 32.2% and 32.2% for probit, *biprobit*, and *mvprobit* respectively.

Table 6 presents the results of the propensity score analysis of current use of modern contraception on exposure to the *Ghati Heri Haad Nilaun* radio drama. The average treatment effect on the exposed individuals, calculated by summing the weighted difference between exposed and unexposed across the eight blocks, was 8.6%. As seen in Figure 4, the treatment effect estimated by all estimation methods was quite consistent (8.5-8.6%), with exception of the simple probit method, which predicted a lower effect (6.21%)

Case #3 *Assessment of treatment effect when exposure is endogenous: Exposure to any mass media in Tanzania*

In Case #3, we use a dichotomous variable capturing whether respondents recalled having heard a family planning message from three common mass media sources: radio, television or newspapers/magazine. Although the TRCHS-99 recorded exposure to FP from other sources (poster, brochure, live drama, community event billboard), the current analysis limits the exposure variable to the mass media channels most commonly used worldwide. The analysis was also limited to these three sources because questions regarding exposure to family planning from radio, television, and newspapers are standard in many Demographic and Health Survey questionnaires— whereas exposure from the specific sources included in the Tanzania survey are not commonly included in other surveys.

Close to 50% of women reported having been exposed to at least one of the three mass media sources (Table 1). The most common source of information about FP was radio (42%), followed by a newspaper or magazine (13%) and television (6%). Among those hearing about FP from the three mass media sources cited above, 62% reported exposure to only one source, 26% reported two sources and 12% reported all three sources.

Examination of the potential endogeneity of exposure to information of family planning on current use of modern contraceptive methods was conducted by using the two SEM methodologies (*biprobit* and *mvprobit*) with a single instrumental variable (listening to the radio weekly) that was significant in the exposure equation, but was not significant in the outcome equation. The other two instrumental variables used in Case #1 (watching television weekly and the village having an all year road) were not valid in Case #3. In both SEM methodologies, the null hypothesis of exogeneity of exposure was rejected at the 0.05 level (Table 7), and thus exposure was found to be endogeneous in the contraceptive use equation.

Exposure to information about family planning through mass media was significant in the simple probit estimation at the 0.10 significance level, and at the 0.001 level in the bivariate probit models. In all three estimation methods, age, marital status and asset quintile were all significantly and positively associated with current use of modern contraception (as compared to the reference category). Education was also significantly and positively associated with contraceptive use and living in a rural area was significantly and negatively associated with contraceptive use (at the <0.10 level). Among the community variables, having a community based distributor was the only variable to be significantly associated with contraceptive use.

Figure 5 shows the predicted probabilities of contraceptive use by each method of estimation. Exposure to mass media notably increased current modern contraceptive use, particularly when using SEM methods that control for the endogenous relationship between the exposure and the outcome. As seen in Figure 5, simulating full exposure increases current modern contraceptive use to 20.0% by the probit estimation model, to 25.7% by the *biprobit* maximum likelihood estimation, and to 25.2% by the *mvprobit* simulated maximum likelihood estimation. The absence of the program reduced the current use of modern contraceptives to 14.5%, 10.0% and 10.3% for probit, *biprobit*, and *mvprobit* respectively.

Table 8 presents the results of the propensity score analysis of current use of modern contraception on exposure to family planning through mass media sources. The average treatment effect on the exposed individuals was calculated as 6.8%. As seen in Figure 6, the treatment effect estimated by propensity score analysis was closer to that estimated by the simple probit command (5.5%), as compared to the SEM models (15.7% and 14.9% for biprobit and mvprobit respectively). The key result for Case #3 is that simple estimation methods and propensity score matching methods can significantly under-estimate the actual effects of exposure when exogeneity is incorrectly assumed.

Conclusion

In this paper, we have examined estimates of the impact of family planning health communication programs on the likelihood that women of reproductive age use modern contraception. Data came from two large nationally representative cross sectional surveys of women's reproductive health and family planning history in Tanzania and Nepal. These data sets are typical of demographic and health data commonly available for developing countries and commonly used in the evaluation of health programs. For the purposes of evaluation, however, these data, while using random samples of the population, do not reflect random distributions of health programs. Identification of "treatment" and "control" groups benefiting or not benefiting from health programs, including health communication programs, rely upon self-reports and likely self-selection processes that are decidedly non-random, potentially affected by myriad observable and unobservable factors. Estimates of health program impacts therefore require the use of methodologies that are appropriate and robust for use with non-experimental data. Two methods for analyzing non-experimental data were used here: propensity score matching methods and regression-based methods with and without controls for self-selection processes.

The econometrics and treatment literature is clear about the conditions and assumptions upon which estimations of treatment effects using simultaneous equations methods and matching estimators are valid in the determination of treatment effects from participation in a program. A key assumption of propensity score matching, and single-equation regression models with binary measures of treatment, is that treatment and control groups differ only along observable characteristics, that is, the non-random process of selection into the treatment group is "ignorable."

From our analysis, several clear conclusions emerge:

1. As expected, single equation regression models and propensity score matching estimators produce generally similar estimates of the impact of health communication programs when exposure to communications programs are exogenous. On the other hand, when researchers naïvely assume exogeneity, treating non-experimental data as if differences in exposed and unexposed individuals are equivalent subject to a limited set of control variables, estimates of the impact of health communication programs can be substantially biased.

2. We cannot know *a priori* whether the process by which individuals report exposure to mass media messages will be statistically independent of the process determining a program outcome, conditional upon observed characteristics of respondents. That is, we cannot know ahead of time whether exposure to health communication messages will be endogenous in models of family planning outcomes. Such conclusions are

likely to be determined by the underlying data and processes at work in the countries under study.

3. Because of the divergence of results from the different estimation methods under different exogeneity scenarios, there is a clear need for researchers to conduct tests for endogeneity. Tests for endogeneity are readily available when potentially endogenous regressors follow a continuous distribution (Rivers and Vuong 1988, Bollen, Guilkey and Mroz 1995), but are less robust when endogenous regressors are binary. Tests for endogeneity require valid exclusion restrictions, that is, variables that uniquely affect participation or exposure but not outcomes. It should be noted that these exclusion restrictions, while grounded in theory and logic, are also likely to be specific to the sample and country under study. That is, instrumental variables that work in one context or one country (or even one time period in one country) may not work elsewhere. Further, it is impossible to know *a priori* which variables will serve as valid exclusion restrictions in the identification of program exposure and program effect. In this analysis, we have used a variety of variables as exclusion restrictions in our models, including ownership of televisions and radios, frequency of use of common media, and distinct community characteristics. Further, while we did not present the results here, the variety of exclusion restrictions used reflected the fact that tests for endogeneity were extremely sensitive to the exclusion restrictions included. This has important implications for evaluators in designing surveys. Evaluators are not able to know beforehand which instrumental variables will work in a particular situation, forcing them to include in survey questionnaires items that may seem to have little programmatic importance but large post-survey analytical value.

4. In a similar fashion, we experienced considerable difficulty in achieving balance in the conditional distributions of observed covariates within blocks using the propensity score method. In at least one case, propensity scores were constructed using different variables that ultimately led to substantially different estimates of the effects.

5. Finally, in the absence of true experiments, we cannot know the exact magnitude of the bias introduced by using simple methods that assume that exposure is random or determined by largely observable processes. Our examples here indicate that the size of the differences across estimation methods can be substantial. For practical purposes, it is important to have a good idea of the magnitude of the difference between estimates of mass media's effects when propensity score methods are used relative simultaneous equations methods. Similar estimates using different methods provide comfort. Divergent results can invoke considerable consternation.

This paper is intended largely to contribute further to the debate regarding appropriate methods for the evaluation of full coverage health communication programs. The results are illustrative of both the gains from rigorous attention to appropriate methodologies and the potential hurdles faced by evaluators seeking to apply those methodologies. Several avenues for additional investigation are readily apparent. For example, future work should examine alternative matching estimators, in particular the Rosenbaum bounds estimator (Rosenbaum 2002, DiPrete and Gangl 2004), to determine the sensitivity of evaluations to the specific matching estimation technique used and to assumptions of exogeneity. Additionally, we suggest further exploration of other regression-based non-parametric and semi-parametric estimators that allow for more flexible modeling of the common unobservable factors affecting exposure to health communication programs and behavioral outcomes.

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Table 1. Socio-demographic characteristics, Tanzania 1999

Variables	(%) n=3826
Currently using a modern contraceptive method	15.7
Listened to Zinduka!	33.2
Heard about FP from any source (radio, television, newspaper)	49.0
Age	
15-19	22.3
20-24	20.4
25-29	18.6
30-34	12.1
35-39	11.3
40-44	7.5
45-49	7.7
Highest Education	
None	27.5
Primary	67.1
Secondary	5.3
Marital Status	
Never Married	23.3
Married	65.9
Separated/Divorced	10.9
Asset Quintile	
Lowest	17.2
2nd Lowest	18.2
Middle	20.2
2nd Highest	19.5
Highest	24.9
Muslim Religion	33.8
Lives in Rural area	71.6
CBD in Community	21.1
HA or VHW visits Community	57.6
Health Center within 5 km	56.6
Listens to radio weekly	27.5
Watches TV weekly	4.3
Village has all year road	66.4

Table 2: Estimation results: Exposure to Zinduka! and Use of Modern Contraception, Tanzania 1999

Variables n=3826	Heard Zinduka! in past 6 months			Current use of Modern Contraception (Probit)			Current use of Modern Contraception (BiProbit)			Current use of Modern Contraception (MvProbit)		
	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat
Listened to Zinduka!				0.3584	0.0999	3.59	0.6327	0.1962	3.22	0.5650	0.1593	3.55
Age (omitted='15-19')												
20-24	-0.0247	0.1116	-0.22	0.6033	0.1333	4.53	0.6012	0.1328	4.53	0.6047	0.1321	4.58
25-29	-0.0834	0.1682	-0.5	0.3534	0.1370	2.58	0.3564	0.1365	2.61	0.3581	0.1376	2.6
30-34	-0.1757	0.1327	-1.32	0.4384	0.1361	3.22	0.4507	0.1354	3.33	0.4507	0.1378	3.27
35-39	-0.0896	0.1311	-0.68	0.5276	0.1579	3.34	0.5324	0.1605	3.32	0.5362	0.1600	3.35
40-44	-0.1658	0.1749	-0.95	0.5097	0.1691	3.01	0.5181	0.1670	3.1	0.5205	0.1663	3.13
45-49	-0.1902	0.1542	-1.23	0.4225	0.1509	2.8	0.4355	0.1512	2.88	0.4377	0.1520	2.88
Education in yrs	0.0968	0.0117	8.27	0.0669	0.0147	4.54	0.0588	0.0160	3.66	0.0613	0.0147	4.17
Marital Status (omitted= 'never married')												
Married	0.3204	0.1569	2.04	0.4160	0.1282	3.25	0.3868	0.1313	2.95	0.3932	0.1295	3.04
Separated/Divorced	0.3544	0.1019	3.48	0.4930	0.1784	2.76	0.4583	0.1907	2.4	0.4644	0.1893	2.45
Asset Quintile (omitted= "Lowest")												
2nd Lowest	0.4624	0.1824	2.53	0.2977	0.1507	1.98	0.2708	0.1431	1.89	0.2818	0.1434	1.97
Middle	0.2932	0.0994	2.95	0.2323	0.1355	1.71	0.2176	0.1310	1.66	0.2248	0.1304	1.72
2nd Highest	0.5450	0.1207	4.52	0.4302	0.1426	3.02	0.3993	0.1313	3.04	0.4180	0.1326	3.15
Highest	0.4591	0.1414	3.25	0.4704	0.1686	2.79	0.4428	0.1662	2.66	0.4617	0.1628	2.84
Muslim Religion	0.4304	0.1270	3.39	0.0536	0.1050	0.51	0.0172	0.0962	0.18	0.0272	0.0975	0.28
Lives in Rural area	-0.2766	0.1425	-1.94	-0.2444	0.1412	-1.73	-0.2098	0.1281	-1.64	-0.2187	0.1280	-1.71
CBD in Community	---	---	---	0.1669	0.0919	1.82	0.1657	0.0910	1.82	0.1663	0.0912	1.82
HA or VHW visits	---	---	---									
Community				0.0026	0.0882	0.03	0.0025	0.0888	0.03	0.0027	0.0891	0.03
Distance in km to HC	---	---	---	-0.0063	0.0103	-0.61	-0.0064	0.0104	-0.62	-0.0064	0.0104	-0.61
Listens to radio weekly	0.9404	0.0860	10.94	0.1067	0.0984	1.08	---	---	---	---	---	---
Watches TV weekly	-0.2695	0.1155	-2.33	-0.0463	0.1289	-0.36	---	---	---	---	---	---
Village has all year road	0.2804	0.1374	2.04	0.0114	0.1141	0.1	---	---	---	---	---	---
Constant	-1.9262	0.2282	-8.44	-2.5159	0.2870	-8.77	-2.4974	0.2417	-10.33	-2.5059	0.2418	-10.37
rho							-0.1594	0.1391		-0.1147	0.1138	-1.01
							Wald test of rho=0:			LL ratio test of rho21 = 0:		
							chi2(1) = 1.269			chi2(1) = 58257.2		
							Prob > chi2 = 0.2600			Prob > chi2 = 0.0000		

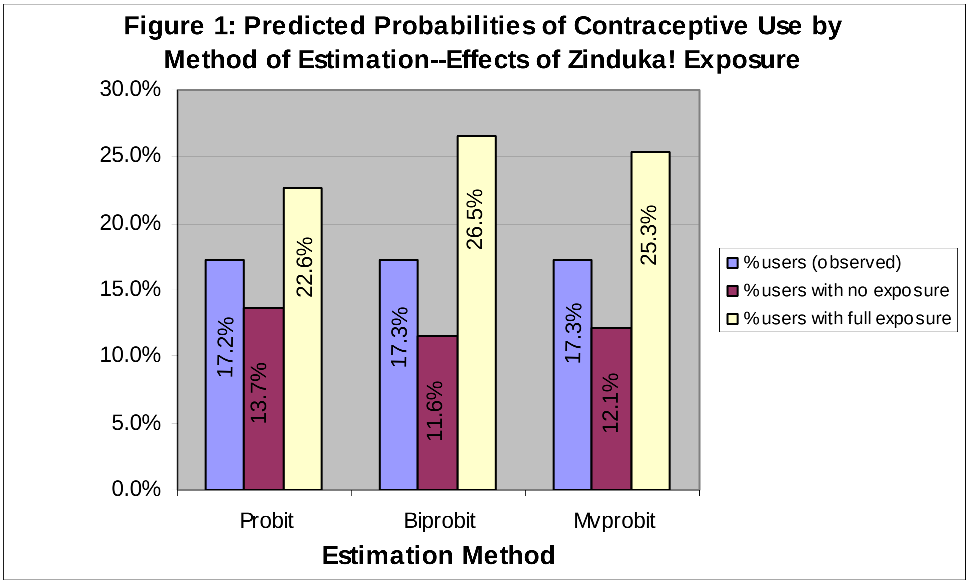
Figure 1: Predicted Probabilities of Contraceptive Use by Method of Estimation--Effects of Zinduka! Exposure
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
17.2%
13.7%
22.6%
17.3%
11.6%
26.5%
17.3%
12.1%
25.3%
Probit
Biprobit
Mvprobit
Estimation Method
%users (observed)
%users with no exposure
%users with full exposure

Table 3. Estimates of the increase in contraceptive use, results from propensity score stratification, Tanzania 1999

P-score Group	% users (unexposed)	% users (exposed)	Diff (unexposed-exposed)	Number of exposed users	weight	Weighted Difference
1	0	0	0	0	0.0008	0
2	0.0415	0.0769	0.0354	78	0.0625	0.0022
3	0.0816	0.1649	0.0833	97	0.0777	0.0065
4	0.1086	0.1983	0.0897	116	0.0929	0.0083
5	0.1281	0.2761	0.1480	163	0.1305	0.0193
6	0.1421	0.2458	0.1037	297	0.2378	0.0247
7	0.1459	0.3079	0.1620	341	0.2730	0.0442
8	0.3171	0.3185	0.0014	157	0.1257	0.0002
Total				1249		**0.1054**

Figure 2: Magnitude of Effects of Zinduka! by Method of Estimation

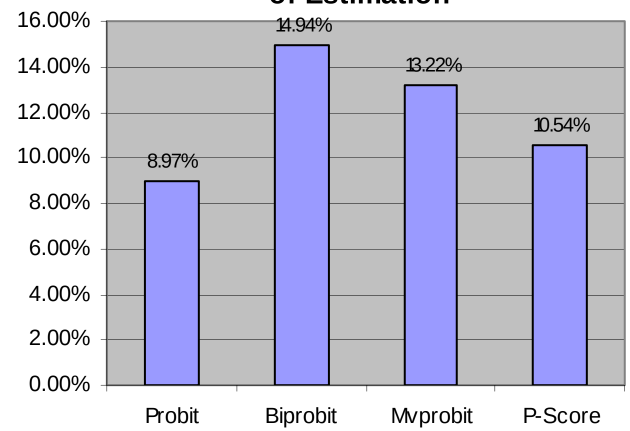

Table 4: Socio-demographic characteristics, Nepal 2001

Variables	(%) n=8429
Currently using a modern contraceptive method	34.5
Listened to *Ghati Heri Haad Nilaun*	34.1
Age	
15-19	10.9
20-24	19.3
25-29	19.2
30-34	16.4
35-39	13.4
40-44	11.5
45-49	9.2
Highest Education	
None	71.6
Primary	14.8
Secondary	12.3
Higher	1.2
Marital Status	
Married	96.9
Separated/Divorced	3.1
Asset Quintile	
Lowest	25.0
2nd Lowest	19.8
Middle	17.8
2nd Highest	19.3
Highest	18.0
Religion	
Hindu	85.5
Muslim	4.5
Buddhist	7.2
Other Religion	2.7
Lives in Rural area	90.4
Visited by a FP worker in last 12 months	10.6
Currently employed	82.9
Number of living children	
None	12.1
1-3	55.2
4-6	28.7
More than 6	4.0
Husbands education	
None	35.6
Primary	25.5
Secondary	32.2
Higher	6.7
Listens to radio weekly	39.1

Table 5: Estimation results, Exposure to *Ghati Heri Haad Nilaun* and Use of Modern Contraceptive Methods, Nepal 2001

Variables n=8429	Heard *Ghati Heri Haad Nilaun* in past 6 months			Current use of Modern Contraception (Probit)			Current use of Modern Contraception (BiProbit)			Current use of Modern Contraception (MvProbit)		
	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat
Listened to *Ghati Heri Haad Nilaun*				0.1767	0.0416	4.24	0.2672	0.0963	2.78	0.2625	0.0982	2.67
Age (omitted='15-19')												
20-24	0.0049	0.0675	0.07	0.3587	0.0647	5.54	0.3582	0.0643	5.57	0.3581	0.0644	5.56
25-29	-0.0875	0.0688	-1.27	0.7162	0.0681	10.52	0.7179	0.0679	10.57	0.7177	0.0679	10.56
30-34	-0.0180	0.0770	-0.23	0.9707	0.0832	11.66	0.9707	0.0831	11.68	0.9708	0.0831	11.68
35-39	-0.1053	0.0824	-1.28	1.0446	0.0925	11.29	1.0463	0.0923	11.34	1.0463	0.0923	11.33
40-44	-0.0276	0.0852	-0.32	0.8544	0.0982	8.70	0.8548	0.0980	8.72	0.8548	0.0981	8.72
45-49	-0.1040	0.0928	-1.12	0.5460	0.1036	5.27	0.5484	0.1037	5.29	0.5485	0.1037	5.29
Education in yrs	0.0640	0.0084	7.60	0.0097	0.0072	1.35	0.0079	0.0074	1.06	0.0080	0.0076	1.06
Asset Quintile (omitted= "Lowest")												
2nd Lowest	0.2890	0.0615	4.70	0.1901	0.0583	3.26	0.1844	0.0596	3.09	0.1856	0.0594	3.12
Middle	0.0413	0.0736	0.56	0.3862	0.0709	5.45	0.3857	0.0709	5.44	0.3862	0.0708	5.45
2nd Highest	0.4178	0.0738	5.66	0.3509	0.0682	5.14	0.3415	0.0723	4.72	0.3429	0.0721	4.75
Highest	0.4565	0.1026	4.45	0.5252	0.0838	6.27	0.5147	0.0874	5.89	0.5161	0.0875	5.90
Religion (omitted=Hindu)												
Muslim	-0.8516	0.1747	-4.88	-0.8624	0.1506	-5.73	-0.8508	0.1502	-5.66	-0.8514	0.1505	-5.66
Buddhist	0.1119	0.0962	1.16	-0.0397	0.0951	-0.42	-0.0424	0.0942	-0.45	-0.0422	0.0944	-0.45
Other Religion	0.2455	0.1349	1.82	-0.3550	0.1534	-2.31	-0.3608	0.1557	-2.32	-0.3605	0.1555	-2.32
Lives in Rural area	0.1243	0.1397	0.89	-0.1676	0.0643	-2.61	-0.1710	0.0647	-2.64	-0.1706	0.0648	-2.63
Visited by FP worker in past 12 mo.	0.0330	0.0677	0.49	0.1851	0.0522	3.54	0.1844	0.0521	3.54	0.1845	0.0522	3.54
Currently employed	0.5700	0.0697	8.17	0.1380	0.0482	2.87	0.1244	0.0497	2.50	0.1253	0.0497	2.52
Number of living children	-0.0079	0.0127	-0.62	0.1153	0.0126	9.15	0.1154	0.0126	9.14	0.1154	0.0126	9.14
Husband's Education (omitted=none)												
Primary	---	---	---	0.1688	0.0444	3.80	0.1690	0.0443	3.82	0.1691	0.0443	3.82
Secondary	---	---	---	0.1505	0.0471	3.20	0.1508	0.0470	3.21	0.1510	0.0470	3.21
Higher	---	---	---	0.2737	0.0851	3.22	0.2747	0.0849	3.24	0.2752	0.0847	3.25
Watches TV weekly	---	---	---	0.3140	0.0491	6.39	0.3149	0.0491	6.41	0.3151	0.0491	6.42
Listens to radio weekly	1.1879	0.0497	23.91	0.0417	0.0420	0.99	---	---	---	---	---	---
Constant	-1.8206	0.1640	-11.10	-1.9354	0.1088	-17.79	-1.9291	0.1085	-17.78	-1.9298	0.1084	-17.81
rho							-0.0515	0.0563	---	-0.0482	0.0585	-0.82
							Wald test of rho=0: chi2(1) = 0.8360 Prob > chi2 = 0.3605			LL ratio test of rho21 = 0: chi2(1) = 1.7e+10 Prob > chi2 = 0.0000		

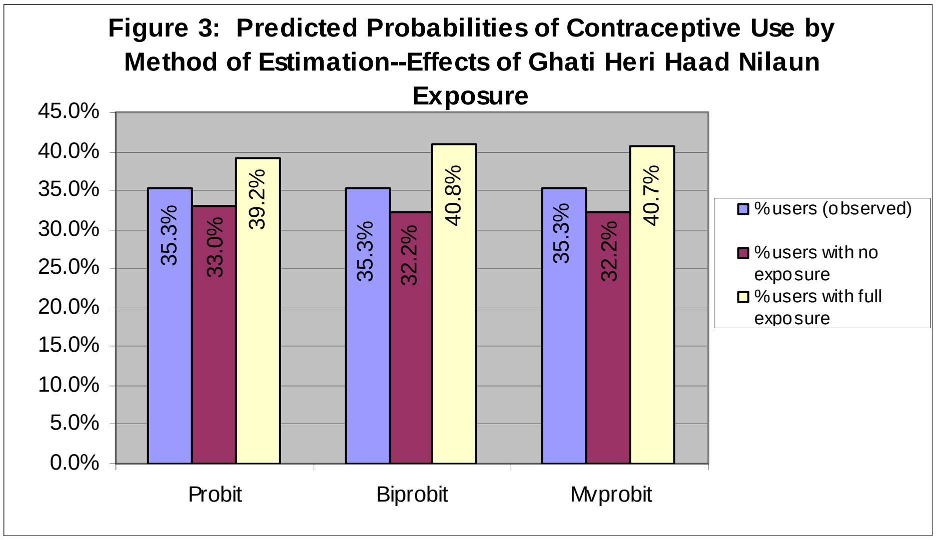
Figure 3: Predicted Probabilities of Contraceptive Use by Method of Estimation--Effects of Ghati Heri Haad Nilaun Exposure
45.0%
40.0%
35.0%
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
35.3%
33.0%
39.2%
35.3%
32.2%
40.8%
35.3%
32.2%
40.7%
Probit
Biprobit
Mvprobit
%users (observed)
%users with no exposure
%users with full exposure

Table 6: Estimates of increase in contraceptive use, results from propensity score stratification, Nepal 2001

P-score Group	% users (unexposed)	% users (exposed)	Diff (unexposed-exposed)	Number of exposed users	weight	Weighted Difference
1	0.2572	0.4286	0.1714	77	0.02607518	0.004469285
2	0.3279	0.4641	0.1362	153	0.05181172	0.007056756
3	0.4354	0.543	0.1076	186	0.06298679	0.006777379
4	0.163	0.3158	0.1528	57	0.0193024	0.002949407
5	0.2107	0.2304	0.0197	369	0.12495767	0.002461666
6	0.4015	0.4816	0.0801	299	0.10125296	0.008110362
7	0.3555	0.4432	0.0877	1812	0.61361327	0.053813884
Total				2953		**0.08563874**

Figure 4: Magnitude of Effects of Ghati Heri Haad Nilaun by Method of Estimation

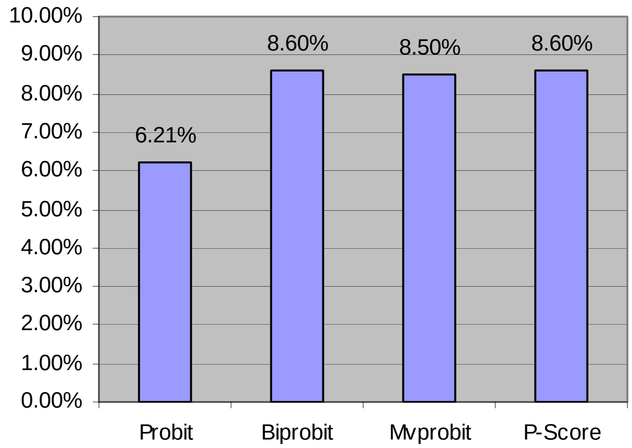

Table 7: Estimation results, Exposure to information about FP on mass media channels and Use of Modern Contraception, Tanzania 1999

Variables n=3825	Exposed to FP on mass media in past 6 months			Current use of Modern Contraception (Probit)			Current use of Modern Contraception (BiProbit)			Current use of Modern Contraception (MvProbit)		
	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat	Coef.	SE	z stat
Exposed to FP on mass media				0.2011	0.1123	1.79	0.6888	0.1858	3.71	0.6553	0.1803	3.64
Age (omitted='15-19')												
20-24	0.2077	0.0935	2.22	0.5885	0.1366	4.31	0.5401	0.1357	3.98	0.5439	0.1343	4.05
25-29	0.1824	0.1193	1.53	0.3490	0.1390	2.51	0.3098	0.1289	2.40	0.3139	0.1298	2.42
30-34	0.0663	0.1350	0.49	0.4193	0.1426	2.94	0.3985	0.1373	2.90	0.4008	0.1380	2.9
35-39	0.3238	0.1254	2.58	0.5080	0.1512	3.36	0.4486	0.1538	2.92	0.4521	0.1569	2.88
40-44	0.1527	0.1284	1.19	0.4835	0.1683	2.87	0.4483	0.1635	2.74	0.4500	0.1644	2.74
45-49	0.0743	0.1269	0.59	0.3950	0.1539	2.57	0.3740	0.1492	2.51	0.3769	0.1497	2.52
Education in yrs	0.0811	0.0100	8.14	0.0699	0.0141	4.94	0.0563	0.0152	3.69	0.0574	0.0154	3.73
Marital Status (omitted= 'never married')												
Married	0.2799	0.0963	2.91	0.4234	0.1234	3.43	0.3741	0.1245	3.00	0.3788	0.1231	3.08
Separated/Divorced	0.3392	0.1225	2.77	0.4980	0.1777	2.80	0.4358	0.1965	2.22	0.4409	0.1953	2.26
Asset Quintile (omitted= "Lowest")												
2nd Lowest	0.1542	0.1231	1.25	0.3285	0.1572	2.09	0.2993	0.1500	2.00	0.3021	0.1502	2.01
Middle	0.0992	0.1013	0.98	0.236	0.1373	1.77	0.2245	0.1336	1.68	0.2242	0.1349	1.66
2nd Highest	0.5497	0.1064	5.17	0.4373	0.1471	2.97	0.3360	0.1378	2.44	0.3461	0.1386	2.5
Highest	0.5487	0.1341	4.09	0.4606	0.1670	2.76	0.3559	0.1777	2.00	0.3662	0.1785	2.05
Muslim Religion	0.2253	0.0971	2.32	0.0817	0.1029	0.79	0.0440	0.0919	0.48	0.0484	0.0930	0.52
Lives in Rural area	-0.2250	0.1179	-1.91	-0.2746	0.1445	-1.90	-0.2322	0.1366	-1.70	-0.2367	0.1359	-1.74
Watches TV weekly	0.1403	0.1407	1	-0.0741	0.1223	-0.61	-0.0837	0.1186	-0.71	-0.0806	0.1185	-0.68
CBD in Community	---	---	---	0.1858	0.0945	1.97	0.1830	0.0922	1.98	0.1838	0.0927	1.98
HA or VHW visits Community	---	---	---	0.0073	0.0892	0.08	0.0059	0.0872	0.07	0.0059	0.0873	0.07
Distance in km to HC	---	---	---	-0.0066	0.0109	-0.61	-0.0065	0.0106	-0.61	-0.0064	0.0106	-0.61
Village has all year road	---	---	---	0.0321	0.1165	0.28	0.0316	0.1139	0.28	0.0310	0.1139	0.27
Listens to radio weekly	0.9861	0.0772	12.77	0.1026	0.1026	1.58	---	---	---	---	---	---
Constant	-1.4159	0.1548	-9.15	0.2903	0.2903	-8.65	-2.4794	0.2789	-8.89	-2.4825	0.2805	-8.85
rho							-0.2907	0.1398		-0.2682	0.1395	-1.9200
							Wald test of rho=0: chi2(1) = 3.842 Prob > chi2 = 0.0500			LL ratio test of rho21 = 0: chi2(1) = 61196.6 Prob > chi2 = 0.0000		

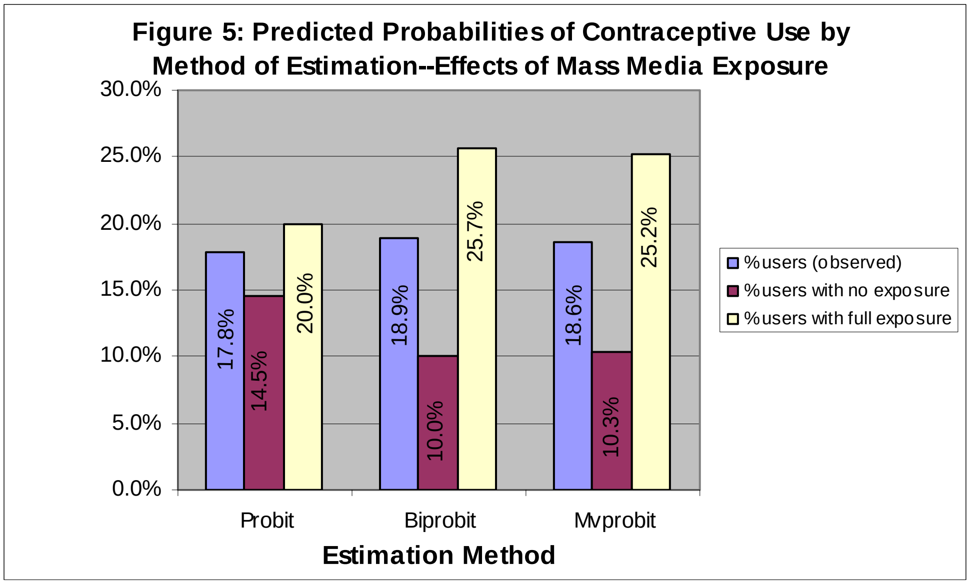
Figure 5: Predicted Probabilities of Contraceptive Use by Method of Estimation--Effects of Mass Media Exposure
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
17.8%
14.5%
20.0%
18.9%
10.0%
25.7%
18.6%
10.3%
25.2%
Probit
Biprobit
Mvprobit
Estimation Method
%users (observed)
%users with no exposure
%users with full exposure

Table 8: Estimates of increase in contraceptive use, results from propensity score stratification, Tanzania 1999

P-score Group	% users (unexposed)	% users (exposed)	Diff (unexposed-exposed)	Number of exposed users	weight	Weighted Difference
1	0.0135	0.0571	0.0557	70	0.03731343	0.001626866
2	0.0886	0.1312	0.0426	404	0.21535181	0.009173987
3	0.1774	0.2581	0.0807	399	0.21268657	0.017163806
4	0.0333	0.0562	0.0229	89	0.04744136	0.001086407
5	0.1481	0.2222	0.0741	171	0.09115139	0.006754318
6	0.1500	0.1626	0.0126	203	0.10820896	0.001363433
7	0.1064	0.2148	0.1084	135	0.07196162	0.00780064
8	0.2286	0.3267	0.0981	202	0.10767591	0.010563006
9	0.2222	0.3350	0.1128	203	0.10820896	0.01220597
Total				1876		**0.06773843**

Figure 6: Magnitude of Effects of Mass Media Exposure to FP by Method of Estimation