Health Care Provider Choice in Rural India

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Quantifying the determinants of health care provider choice can give important guidelines for health policy intervention in developing countries like India. This paper tries to do that by modeling the choice of health care providers in rural India in a mixed multinomial logit framework. The role of individual specific taste heterogeneity is explicitly taken into consideration in this framework. We use data from 1996 nationwide health survey conducted by National Sample Survey Organization (NSSO) of India. Since NSSO data do not provide the prices of the healthcare providers that an individual did not visit, the method of multiple imputation is used to impute the prices of those providers. Simulated maximum likelihood method is used to estimate the model parameters. Estimated results show that price and distance play important roles in health care provider choice. The modeling strategy allows to capture the fact that people may like to travel longer distance to access better care. Price elasticity of demand for health care is higher for people in the lower income groups than those in the higher income groups. Moreover, children are more price-sensitive than adults which is perhaps reflective of the socio-economic structure of a typical household in rural India where an adult's health is more important than that of the child for the household's economic sustenance.

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1. INTRODUCTION

Indian health sector comprises of both public and private initiatives. Public sector includes government hospitals for urban areas and a three-tiered system of health infrastructure for the rural areas consisting of sub-centers, primary health centers (PHC) and community health centers (CHC). The private health sector in India comprises of private hospitals and private doctors. Unqualified rural medical practitioners (RMP) and self-medication also coexist along with the formal health care practice.

Health care in public hospitals is either free or highly subsidized, which partly reflects Indian government's commitment to provide universal health care. Private health care providers, on the other hand, charge user fee. Similarly care from RMPs and self-medication also do not come free. Thus one would expect that people have incentive to use government hospitals more for their health care needs than non-government providers, which include

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private care, RMPs and self-medication. However, this is not the case in practice. As Mishra et al. (2003) report that private health sector accounts for approximately 82 and 55 percent of outpatient and inpatient visits in India respectively, while an estimated one million RMPs, which are generally active in rural areas, take care of minor illnesses. This suggests that besides monetary cost (e.g., user fee), there are some non-monetary costs (such as distance to the provider, quality of care, waiting time etc.) associated with a provider type that also influence the choice of health care provider by an individual.

The primary objective of this paper is to quantify the determinants of demand for health care from different provider types in rural India. This question is important because it directly influences an individual's choice of health care provider. Specific numbers on the determinants of demand for health care would provide useful guidelines to the policy makers for health policy intervention. The model that we develop provides the theoretical framework for understanding the individual choice decision on health care provider types. We analyze the demand for health care from different provider types in a mixed logit framework, which results from a more general individual utility-maximizing framework known as random utility framework (RUM). Besides the observable determinants of demand for health care like price, health status, distance to the provider etc.), unobserved (to the analyst) factors such as quality of care from a provider, individual perception towards a provider etc. can also be accommodated in this framework. Modeling unobserved heterogeneity in this way allows a flexible substitution pattern between alternative providers and results in more reliable estimates of the determinants of demand.

We do not consider health care provider choice by the urban population because information on distance from an urban household to a specific provider is not available in the NSSO (1996) data used for this study.[3] The same data concern restricts this study to only three major provider types: government, private hospitals and private doctors. RMPs and self-medication are out of the scope of the present study because distance information for these sources is not included in the survey. Since NSSO data do not provide the prices of the health care providers that an individual did not visit, the method of multiple imputation is used to impute the prices of those providers.

Previous studies in this direction include Gertler et al. (1987), Mwabu et al. (1993) and Gertler and van der Gaag (1990), all of which study demand for health care in developing countries. The common findings in all these studies include i) user fee and distance are important determinants of demand for health care and ii) price elasticity of demand for

[3] Acton (1982) finds that distance is an important non-monetary factor in the demand for health care.

health care decreases as income rises. A recent study by Sarma (2003) who uses the same NSSO data as the present work. His findings also confirm those of the above authors. All of these studies differ from our work in that they all use nested logit framework to model the demand for care. As explained in subsection 2.2, this modeling strategy has some important limitations, which might result in unreliable estimates. Harris and Keane (1999) use a similar model like ours in the context of health insurance plan choice. To our knowledge, the health care provider choice has not been studied earlier in a mixed logit framework, which is more general and gives rise to nested logit as a special case (Brownstone and Train (1999)). Thus the present work fills this gap in the literature.

The remainder of the paper is organized as follows. In Section 2, we model the choice of health care provider by an individual and cast the problem in random utility framework leading to a mixed logit model. Section 3 describes the data source and briefly explains the multiple imputation technique used to impute the missing data. We report our empirical results in Section 4. Section 5 gives some concluding remarks and also indicates some future directions of research.

2. THE MODEL

Individual n faces $J_n + 1$ alternative health care providers. The short-run conditional utility of receiving care from provider j is

$$U_{nj} = U(C_{nj}, H_{nj}), \ \ j = 0, 1, 2, ..., J_n, \tag{1}$$

where C_{nj} is consumption of composite goods other than medical care after paying for the cost of provider j and H_{nj} is the expected level of improvement in individual n's health status after receiving treatment from provider j. Utility is assumed to be stable in the sense that it does not change from time to time with new information and the usual assumptions are made about the utility function: $U_c > 0, U_{cc} < 0, U_h > 0$ and $U_{hh} < 0$.[4] The production function for health is assumed to be $H(m_{nj})$, where $m_{nj} > 0$ is the medical care that an individual n receives from provider j, with $H'(.) > 0, H''(.) < 0$. Thus the health production function is assumed to exhibit diminishing marginal product with respect to medical care.[5] The implicit assumption underlying the above specification of the health production function is that individual n uses medical care to produce an improvement H_{nj} in health status as compared to no treatment or self treatment which produces an improvement H_{n0} in health status.

[4] See Phelps (2003, p. 101) for stable utility function in health care.

[5] This is in order to accommodate the possibility of "iatrogenic illness" (See Phelps, 2003, p. 97).

Medical care, on the other hand, is assumed to depend on both observed and unobserved characteristics of the provider and the individual seeking care. Observed attributes of the provider include the user fee and the distance that an individual has to travel to access care from the provider. Unobserved attributes of the provider include, among other things, the reputation of the provider as a care giver, the hospitality of the medical staff, physician specialty, the degree of cleanliness and hygiene maintained in the provider's clinic etc., which are not observed by the analyst. Examples of individual observed characteristics that might influence the usage of medical care are age, sex, education, social group, health status and so on, while unobserved characteristics might include her tastes or liking for certain attribute of the provider, perception of the quality of care from a provider etc. Thus we can specify medical care as a log-linear function of the observed and unobserved attributes of the providers as well as the individuals, $\ln m_{nj} = \theta_j + \boldsymbol{\gamma}_n \mathbf{X}_{nj} + \omega_{nj}$, where $\mathbf{X}_{nj}$ denotes the vector of observed attributes of the alternative j and interactions of observed individual characteristics with these attributes, θ_j is consumer's valuation of some unobserved attribute of the provider and ω_{nj} is iid mean zero with finite variance σ^2_ω which is assumed to capture the residual uncertainty.[6]

Coefficient vector $\boldsymbol{\gamma}_n$ has components that are either random or fixed. A random coefficient represents random taste of individual n for an observed attribute, say x_{nj}, of the provider j or interaction of some individual characteristics (e.g., age, sex etc.) with the provider attribute x_{nj}. Unlike in standard logit, the random components of the coefficient vector $\boldsymbol{\gamma}_n$ varies in the population across individuals, representing taste differences in the population associated with the relevant attributes. Assuming the health production function to be $H_{nj}(m_{nj}) = \ln m_{nj}$, we have:

$$H_{nj} = \theta_j + \gamma_n X_{nj} + \omega_{nj}. \tag{2}$$

Price p_{nj} of medical care comprises of direct (monetary) payment (e.g., out-of-pocket expenses on user fee, medicines, diagnostic tests etc.) as well as indirect (non-monetary) cost of access (e.g., transportation cost, waiting time etc.). Then the budget constraint of the individual n is:

$$C_{nj} + p_{nj} = Y_n, \tag{3}$$

where Y_n is the income of the individual n and $C_{nj} \geq 0$. In this specification, income affects utility through consumption, and the price of care is the foregone consumption. This

[6] In standard logit formulation, θ_j represents the average impact of omitted variables. In the present formulation, however, it is not entirely the case, as part of the variation due to omitted variables is incorporated in the random coefficients.

specification of income is in line with Gertler and van der Gaag (1990), which allows the inclusion of the value of home production, a major source of income for the rural population in a developing country like India.

Gertler et al. (1987) have shown that in order for income to influence the choice of provider by an individual, the specification of conditional utility must ensure non-constant marginal rate of substitution between health and consumption. Moreover, if health is a normal good, then the conditional utility must be concave in consumption.[7] Therefore we specify a semi-quadratic conditional utility function, which is linear in health and quadratic in consumption, $U_{nj} = \alpha_{n0}H_{nj} + \alpha_{n1}C_{nj} + \alpha_{n2}C_{nj}^2 + \eta_{nj}, (j = 0, 1, 2, ..., J_n; n = 1, 2, ..., N)$, where $C_{nj} = Y_n - p_{nj}$ and η_{nj} is mean-zero iid errors with finite variances σ_η^2, and uncorrelated across individuals as well as across alternatives. Normalizing $\alpha_{n0} = 1$ and substituting H_{nj} from (2), the utility that individual n derives from alternative j is given by $U_{nj} = \theta_j + \boldsymbol{\beta}_n \tilde{\mathbf{X}}_{nj} + \varepsilon_{nj}$, where $\tilde{\mathbf{X}}_{nj} = (\mathbf{X}_{nj}, C_{nj}, C_{nj}^2)$, $\boldsymbol{\beta}_n = (\boldsymbol{\gamma}_n, \boldsymbol{\alpha}_n)$, $\boldsymbol{\alpha}_n = (\alpha_{n1}, \alpha_{n2})$, $\varepsilon_{nj} = \eta_{nj} + \omega_{nj}$ and θ_j is as explained above. Since individual n knows her $\mathbf{X}_{nj}$, θ_j, $\boldsymbol{\beta}_n$ and ε_{nj} for each j, she chooses alternative j provided $U_{nj} > U_{ni} \forall i \neq j$. However, the analyst does not observe $\theta_j \forall j$ and $\boldsymbol{\beta}_n \forall n$ and thus she wants to estimate these quantities. Note that the coefficient vector $\boldsymbol{\beta}_n$ has some random components representing random tastes of the individual for the associated attributes. The analyst has to specify reasonable distributions for those random taste parameters.

2.1. Random Utility Framework

Assume that an individual n $(n = 1, 2, ..., N)$ maximizes her utility U_{nj} by choosing alternative j from her choice set M_n that is comprised of $J_n + 1$ alternatives, where $M_n = (0, 1, 2, ...J_n)$. Thus utility U_{nj} in (1) can be thought of as being composed of an observed (systematic) part and a random part:

$$U_{nj} = V(X_{nj}; \beta_n) + \varepsilon_{nj}, (j = 0, 1, 2, ..., J_n; n = 1, 2, ..., N), \tag{4}$$

where $V(.,.)$ is the systematic part in individual n's utility, which can be specified as a function of the explanatory variables $\mathbf{X}_{nj}$, representing observed attributes of the alternatives, observed characteristics of the individual n as well as alternative-specific constants; β is the vector of unknown parameters, and ε_{nj} is a random disturbance term. This error term is assumed to capture unobserved (to the researcher) individual characteristics as well as unobserved attributes of the alternative j.[8] In the context of health care provider

[7] See Gertler et al. (1987) and Gertler and van der Gaag (1990) for details on these points.

[8] McFadden (1974) interprets the systematic part as the representative taste of the population and ε as reflecting the

choice, such unmeasured individual characteristics might include taste-heterogeneity of individuals, perception about the quality of care provided by alternative providers, perception about health status etc. while unobserved attributes of a provider might include, among other things, quality of care. Assume $\boldsymbol{\varepsilon}_n$ follows some distribution $D(\boldsymbol{\theta}_\varepsilon)$, where $\boldsymbol{\theta}_\varepsilon$ is the unknown parameter vector that we need to estimate along with other parameters.

In real life, utility U_{nj} remains latent, and therefore an indicator function, y_{nj} (such that $y_{nj} = 1$, if $U_{nj} \geq U_{ni} \forall i \neq j \in M_n$ and $y_{nj} = 0$ otherwise), is used to indicate the observed choice that results from individual utility maximization. Then the probability that individual n chooses alternative j is given by $P_{nj} = P(j|X_n; \beta_n, \boldsymbol{\theta}_\varepsilon) = P(y_{nj} = 1) = P(U_{nj} \geq U_{ni} \forall i \neq j \in M_n)$.

Since the probability that an individual n chooses alternative j is assumed to be independent of her choosing another alternative k $(j \neq k)$ from the choice set M_n, the probability that she chooses any alternative j is given by:

$$P(y_{nj}|X_n; \beta_n, \boldsymbol{\theta}_\varepsilon) = \prod_{j \in M_n} P_{nj}^{y_{nj}}. \tag{5}$$

Assuming that individuals make choices independently, the probability that each of the N persons in the sample chooses an alternative j is given by:

$$L(\beta, \theta_\varepsilon) = \prod_{n=1}^{N} \prod_{j \in M_n} P_{nj}^{y_{nj}}. \tag{6}$$

Equations (4) to (6) constitute the foundation or the kernel of the random utility model (RUM) of discrete choice.[9]

Different assumptions on the error structure lead to different kernels. For example, normal errors give rise to probit kernel while GEV (Generalized extreme value) errors lead to logit kernels. The choice of the kernel is based on computational tractability as well as the nature of the data at hand. In empirical applications, when there are more than three choices, computing probit probabilities becomes cumbersome as it involves multiple integrals. GEV kernel is preferred in such situations because it incorporates flexible error structure as in probit models yet it is computationally more tractable. This is because the additive GEV errors lead to a very simple probability simulator, which is the average of a set of logit probabilities. Thus if disturbances ε_n are assumed to be iid extreme value, the probability of individual n choosing alternative j is given by the simple multinomial logit (MNL) formula: $P_{nj} = P(j|X_n; \beta_n, \theta_\varepsilon) = \frac{e^{V(X_{nj};\beta_n)}}{\sum\limits_{i \in M_n} e^{V(X_{ni};\beta_n)}}$.

idiosyncratic taste of the individual n for alternative j with attributes A_{nj}.

[9] See Walker and Ben-Akiva (2002) for a detailed exposition on kernel of random utility models.

2.2. Mixed Logit Model

Although MNL model described in the previous section provides tractability and closed form for choice probabilities, it suffers from *independence from irrelevant alternatives* (IIA), which ignores substitutability that might exist between alternatives other than the two considered at a time. This is a consequence of the assumption of iid extreme value errors. Nested logit model which uses GEV errors do overcome the problem of IIA and yet provide closed-form expressions for the choice probabilities.[10] But nested logit models require that the researcher has *a priori* knowledge about how to divide the alternatives in mutually exclusive and exhaustive nests so as to model the existing substitution patterns between alternatives. It is, however, not clear whether any nesting pattern that the researcher imposes on the basis of her prior beliefs can fully account for the true substitution pattern.[11] Mixed multinomial logit (MMNL) or simply "mixed" logit model overcomes these pitfalls by introducing a flexible error structure that captures more realistic substitution patterns.[12,13] This can be implemented by assuming that ε_n has iid extreme value and by allowing some or all the coefficients β_n in the individual's utility specification to be random, which follow some non-GEV distribution, $f(\beta_n|\theta_\beta)$. Although $f(\beta_n|\theta_\beta)$ can be theoretically any distribution, the use of normal, lognormal, uniform and triangular are more common in applications (See Bhat (1998), Revelt and Train (1998), Hensher and Greene (2001), Ben-Akiva, Bolduc and Walker (2001), Walker and Ben-Akiva (2002)). The resulting choice probabilities involve multiple integrals, posing similar challenges as in probit models. However, the additive and iid GEV errors lead to a very convenient probability simulator.

Assuming a linear-in-parameters utility function, (4) becomes

$$U_{nj} = \boldsymbol{\beta}_n \mathbf{X}_{nj} + \boldsymbol{\varepsilon}_{nj}, \tag{7}$$

where the $k \times 1$ parameter vector $\boldsymbol{\beta}_n$ is random, whose k^{th} component can be further decomposed as $\beta_{nk} = b_k + \boldsymbol{\delta}'_k \boldsymbol{\omega}_n + \sigma_k \eta_{nk}$ (see Greene and Hensher (2002)). Stacking over k, we get $\boldsymbol{\beta}_n = \mathbf{b} + \boldsymbol{\Delta}\boldsymbol{\omega}_n + \boldsymbol{\Gamma}\boldsymbol{\eta}_n$. Here $\mathbf{b}$ represents the average taste in the population; $\boldsymbol{\omega}_n$ is a vector of choice-invariant characteristics that generates individual heterogeneity in the means of random coefficients $\boldsymbol{\beta}_n$; $\boldsymbol{\Delta}$ is the relevant parameter matrix; $\boldsymbol{\eta}_n$ is the vector of

[10] Nested logit models were independently developed by Ben-Akiva and Lerman (1979) and Daly and Zachary (1979).

[11] See Nevo (2000) for some more expository examples of the failure of the nested logit models to address MNL model's drawbacks such as the dependence of own-price elasticity on the functional form of the indirect utility function.

[12] See Berry (1994) for an explanation of how random parameters in the utility specification overcome the problem of *a priori* imposition of unreasonable substitution effects as seen in simple logit model.

[13] MMNL model is known by various other terminologies including random parameter logit (RPL) model. See Revelt and Train (1998) for a discussion on alternative terminologies for MMNL model. We will use the terminology MMNL model or simply "mixed" logit because the resulting choice probability is a mixture of logit probabilities with a specified mixing distribution.

white noise, the source of random taste variation, which may be assumed to be distributed normally or with some other distribution; and $\mathbf{\Gamma} = diag(\sigma_1, \sigma_2, ..., \sigma_k)$ is a diagonal matrix, implying that the random parameters are not correlated. To allow for correlated parameters, we need to specify $\mathbf{\Gamma}$ as a lower triangular matrix so that the variance-covariance matrix of the random coefficients becomes $\mathbf{\Gamma\Gamma}' = \sum$. Non-random parameters in the model can be easily incorporated in this formulation by specifying the corresponding rows in $\mathbf{\Delta}$ and $\mathbf{\Gamma}$ to be zero. Thus the conditional choice probability that individual n chooses alternative j, conditional on the realization of $\boldsymbol{\eta}_n$, is given by

$$P\left(j|\boldsymbol{\eta}_n, \boldsymbol{\theta}\right) = \frac{\exp\left(\boldsymbol{\beta}_n \mathbf{X}_{nj}\right)}{\sum\limits_{i \in M_n} \exp\left(\boldsymbol{\beta}_n \mathbf{X}_{ni}\right)}, \tag{8}$$

where $\boldsymbol{\beta}_n$ is as defined above, $\boldsymbol{\theta} = (\mathbf{b}, \mathbf{\Delta}, \mathbf{\Gamma})$ and $\boldsymbol{\eta}_n$ follows some distribution D with mean vector $\mathbf{0}$ and variance-covariance matrix $\mathbf{I}$.

The unconditional choice probability P_{nj} that individual n chooses alternative j is given by $P_{nj} = \int_{\boldsymbol{\eta}_n} P\left(j|\boldsymbol{\eta}_n, \boldsymbol{\theta}\right) dF_{\boldsymbol{\eta}}(\boldsymbol{\eta}_n)$, where $F_{\boldsymbol{\eta}}(.)$ is the joint cdf of $\boldsymbol{\eta}_n$. Thus the choice probability under MMNL model can be thought of as a weighted average of standard MNL probabilities with weights given by the mixing cdf $F_{\boldsymbol{\eta}}(.)$. Following (6), the log-likelihood for θ can be evaluated as:

$$\mathcal{L}(\theta) = \sum_{n=1}^{N} \sum_{j \in M_n} y_{nj} \log P_{nj}. \tag{9}$$

2.3. Estimation Strategy

Since the unconditional choice probability P_{nj} involves multi-dimensional integral over the mixing distribution, the log-likelihood function in (9) does not have generally have a closed form. This implies that we can not differentiate the log-likelihood function with respect to the parameter vector $\boldsymbol{\theta}$=$(\mathbf{b}, \mathbf{\Delta}, \mathbf{\Gamma})$ in order to obtain its estimate. One way to overcome this problem is to estimate the choice probability P_{nj} through simulation and then maximize the resulting simulated maximum likelihood (SIML) with respect to the parameter vector. As already observed, MMNL framework offers a tractable, unbiased and smooth simulator[14] for the choice probability, which is given by:

$$\hat{P}_{nj} = \hat{P}(j|\mathbf{X}_n, \boldsymbol{\theta}) = \frac{1}{\mathcal{S}} \sum_{s=1}^{\mathcal{S}} P(j|\mathbf{X}_n, \boldsymbol{\beta}_n^s; \boldsymbol{\theta}), \tag{10a}$$

[14] $\hat{P}_{nj}$ is smooth because it is twice differentiable in the parameters $\boldsymbol{\theta}$ and the variables $\mathbf{X}_n$. This property of the simulator facilitates numerical search for the likelihood function (Train (2003)).

where $\boldsymbol{\beta}_n^s = \mathbf{b} + \boldsymbol{\Delta}\boldsymbol{\omega}_n + \boldsymbol{\Gamma}\boldsymbol{\eta}_n^s$ and $\boldsymbol{\eta}_n^s$ is the s^{th} $(s = 1, 2, ..., S)$ draw from the joint distribution of $\boldsymbol{\eta}_n^s$, i.e., from $f(\boldsymbol{\eta}_n)$ (McFadden and Train (2000)). The choice probability depends on the parameter vector $\boldsymbol{\theta}$=$(\mathbf{b}, \boldsymbol{\Delta}, \boldsymbol{\Gamma})$, which needs to be estimated. By construction, $\hat{P}_{nj}$ in (10a) is an unbiased estimate of the unconditional choice probability $P(i|X_n; \theta_\beta)$ and its variance is a decreasing function of S, the number of replications. Moreover, the fact that it is strictly positive for all S validates the construction of the log-likelihood $\ln(\hat{P}_j)$. It is smooth (i.e., twice differentiable) in parameters as well as in variables, which aid in the numerical search for a ML estimator and also in elasticity computation. The simulated probabilities of all the alternatives add to one and this helps in forecasting (Train (2003)).

The log-likelihood function in (9) can be approximated by the simulated maximum log-likelihood (SIML) given by

$$\mathcal{SL}(\theta_\beta) = \sum_{n=1}^{N} \sum_{j \in C_n} y_{nj} \log \hat{P}_{nj}. \tag{11}$$

It is noteworthy that although $\hat{P}_j$ is unbiased for P_j, $\ln(\hat{P}_j)$ is not unbiased for $\ln(P_j)$, therefore the simulator brings in some bias in the log-likelihood function. However, if the number of simulation, S, increases faster than the square root of the number of observations, this bias disappears asymptotically.[15]

Drawing pseudo-random numbers from the mixing distribution to simulate the choice probability P_{nj} might require a large number of such draws to maintain resulting simulation errors in the parameter estimates at a reasonable level. We therefore employ more efficient non-random but 'intelligent' Halton draws (Bhat (2001), Hensher and Greene (2001) and Train (1999)).

3. THE DATA

As already mentioned in the introduction, the data for this study come from 52nd round of NSSO (NSSO (1996)), which was a countrywide survey focussed on health care and education. Besides health care utilization data, the survey also provides good amount of information on some important socio-economic and demographic variables. However, the survey records price of only the provider that an individual visits. Prices of alternative providers for similar services are not recorded. In order to determine the effect of price on the demand for different provider types under the MMNL framework, we need to impute prices of the alternative providers that an individual did not visit. In setting price, a care

[15] See Lee (1992) and Hajivassiliou and Ruud (1994).

provider would base its decision on observed determinants $\mathbf{w}$ of price, which may include, among other things, the type of ailment, whether adult or child, sex, health status of the individual and number of days for which care has been taken within the reference period. We impute missing prices for different providers by *empirical residual* (ER) method, which was first suggested by Rubin (1987). The basic idea in ER method is to regress the variable with missing observations (price) on a set of predictors for the non-missing cases and then use the estimated regression to predict the missing observations of the variable. Details of the ER imputation method and its implementation in the present study have been withheld due to space constraint. The same can be made available by the author on request.

The survey collects particulars of spells of ailments of household members during the last 15 days preceding the day of the survey. The final sample includes individuals who suffered from and sought care for one of the following three most common diseases during the two-week reference period of the survey: diarrhea and gastroenteritis (including cholera), fevers of short duration, and cough (including acute bronchitis). The size of the final sample is 7686 with 3756 children (age$\leq$16) and 3930 adults. For flexibility in the empirical specification, we model children and adults' health care demand separately. Table 1 describes the variables used in the study while Table 2 provides summary statistics of the same.

The way in which some of the variables used in this study have been constructed merits some explanation. The survey lists nine different provider types, which have been broadly grouped as government hospital ($GvtH$), private hospital ($PvtH$) and private doctor ($PvtD$). General education level is recorded as a categorical variable. For this study, we have reconstructed it to have only two categories: whether the respondent has primary education or not. For children aged ten years or below, education level of the mother is used.[16]

4. EMPIRICAL RESULTS

In order to estimate the model by simulated maximum likelihood method, 500 Halton draws are made for each sampled individual to generate her simulated choice probability. We carry out three imputations and the parameter estimates from these imputations are combined according to multiple imputation methodology. The combined parameter estimates of the mixed logit model are presented in Table 3.[17] Private doctor ($PvtD$) alternative is kept as the base alternative in the estimation and as such the coefficients estimates for other two alternatives should be interpreted relative to private doctor. For comparison, we have also

[16] Glewwe (1999) justifies how mother's education contributes to the health and nutrition of children in developing countries.
[17] The model is estimated by using NLOGIT 3.0 software, developed by Econometric Software, Inc.

estimated a simple multinomial logit model whose estimates are also presented alongside the mixed logit estimates. As we notice from the simulated log-likelihoods at convergence, the mixed logit specification improves the fit of the model for both children and adults. The interpretations that follow are based on the mixed logit estimates. The present specification of the mixed logit model has been obtained after extensive tests on other competing specifications. In deciding between two competing models, the criterion used is adjusted pseudo R-squared.[18]

We allow the coefficients of the distance dummies to be random with normal distribution. These distance dummies are included in the regression to capture the possibility that an individual prefer lesser distance to a health facility to more. Also, these parameters are assumed to be correlated in order to accommodate a more general interalternative substitution pattern. However, the Cholesky decomposition of the variance-covariance matrix of the random coefficients show that such correlation is not tenable in our case.

The appropriate distribution for the coefficient of an attribute depends on whether people like the attribute (positive), dislike it (negative) or remain neutral about it (zero). Since the range of normal distribution is the entire real line, it is an appropriate distribution for the random coefficient of an attribute which is liked by some, disliked by some other and also there some people who do not care about it. Although distance seems like an attribute that is disliked by everyone in the population, in the context of health care, people do not mind visiting a health care provider with good reputation even if it is located at a greater distance. This justifies the assignment of normal distribution to the distance dummies in this study.

The coefficients of the distance dummies have the form $\boldsymbol{\beta}_n = \mathbf{b} + \boldsymbol{\Delta\omega}_n + \boldsymbol{\Gamma\eta}_n$. In Table 3, the coefficients on DIST_j variables estimate $\mathbf{b}$, the average taste for distance in the population, while the estimates of the deep parameters lumped in the vector $\boldsymbol{\Delta}$ are found in the 'Heterogeneity in mean parameters' section of the table. We notice that all the coefficients in $\mathbf{b}$ are significant across alternatives *GvtH* and *PvtH* and also for both children and adults. This implies that distance to the provider plays a significant role in the choice of health care provider. Moreover, the magnitudes of these coefficients support the hypothesis that, on average, people like to visit a health facility that is located at a closer distance. The

[18] Adjusted pseudo R-squared given by $\mathcal{R}^2 = 1 - \frac{\mathcal{L}_1 - k}{\mathcal{L}_0}$, where $\mathcal{L}_1$ is the likelihood of the model being estimated, $\mathcal{L}_0$ is the likelihood of the model with only an intercept term and k is the number of parameters being estimated. It is to be noted that unlike the simple R^2 for linear regression where a higher magnitude implies a better fit of the model to the data, $\mathcal{R}^2$, on the other hand, implies approximate percentage increase in the log-likelihood over the model with only intercepts (since $\mathcal{R}^2 = \frac{\mathcal{L}_0 - \mathcal{L}_1 - k}{\mathcal{L}_0}$). It is, however, not entirely clear how this measure implies goodness of fit although in model comparisons, the model with higher adjusted pseudo R-squared is taken to be a better fit of the data.

'Standard Deviation of Parameter Distributions' section of Table 3 gives the standard deviations of the relevant coefficients. Thus, for example, the coefficient of *DIST4* is distributed as $N(-1.58 + 0.03 \times ILLNU, 1.8^2)$. At mean value of *ILLNU* for children (i.e., 5.63), the probability that this coefficient is positive is approximately 22 percent. This implies that distance of more than 10 kilometers to a government health facility is disliked by about 78 percent of the children population while it is favored by 22 percent of the children population. The same can not be said about other distance coefficients as the estimates of standard deviations are not significant at reasonable levels. For adults, *HSTATUS* enters significantly in the taste heterogeneity for distance. The positive sign for this variable implies that if the ailment prolongs, distance seems to matter less. Intuitively, this is appealing because we know that the current status of health plays a significant role in an individual's perception about distance to a health facility.

The coefficient of net consumption $C = Y - P$ is kept fixed. The fact that C is significant in both children and adult models implies that price of health care plays a crucial role in the choice of health care providers by the rural population in India. We also notice from Table 3 that the coefficient of consumption squared, CSQ, is negative and significant at one percent level of significance for children. The significance of the coefficient of CSQ supports our hypothesis set out in Section 2 that conditional utility is concave in consumption. However, the same is not the case with adults, as the CSQ term does not enter the model with any reasonable level of significance.

Other fixed (non-random) coefficients in the mixed logit model have expected signs. An increase in the household size reduces the probability that an individual chooses either government hospital or private hospital relative private doctor. An additional day of illness increases the probability of choosing private hospital relative to private doctor for both children and adults. This is rather expected in rural India's context as majority of the rural population visits a private doctor than either government or private hospital. This partly reflects the fact that private doctors provide easier access to health care than government or private hospital, which might be due to less distance, familiarity with the village doctor etc. When visiting the private doctor does not bring in any improvement in the health condition, people turn to the private hospitals. A child whose mother has primary education or more has higher probability of visiting a government facility than a child whose mother does not have primary education. Similarly, relative to private doctor, an SC/ST child has a higher probability of visiting government hospital than a general-caste child while an SC/ST adult has higher probability of choosing either government or private hospital than a general-caste adult.[1] A female child has higher probability of visiting both government and private hospital relative to private doctor. The probability of choosing private hospitals over private doctor by both children and adults diminishes with an additional day of treatment within the reference period.

For discrete choice models, marginal effects or derivatives of the choice probabilities with respect to the explanatory variables provide more useful information than the coefficient estimates. Further, a more appealing measure than marginal effects, however, is the elasticity of choice probability, which gives the percentage change in the choice probability of an alternative for a percent change in an attribute of the same or some other alternative. This is because the latter is a unit-free measure.

We first compute the price elasticity of the choice probabilities. Since price of an alternative enters the model non-linearly, elasticity computation by derivative method does not yield a simple form. Therefore we compute arc price elasticity using sample enumeration procedure outlined in Gertler and van der Gaag (1990, p. 85).[19] Table 4 gives estimates of these elasticities for both children and adults associated with four price bands that ranges from free care up to Rs. 500 (approximately US $ 10). If one reads down a column of Table 4, one finds the elasticity for different price ranges, with income remaining fixed. Reading across a row shows how price elasticity changes with income, with price remaining fixed.

It is apparent from Table 4 that people in lower income groups are more price-sensitive in their demand for health care than those in higher income groups. This is true for both children as well as adults. Further price elasticities are generally higher for children than for adults except in the top income quartile. This suggests that a higher price of care affects the poor and children more than the rich and adults. It might be due to the fact that for a poor rural household, the health of an adult member in the family who is likely to be an income-earner is more important than the health of a child. It is also interesting to see how males and females as groups respond to the change in the price of health care as it is often argued that women in India are a subjugated lot as such they suffer disproportionately more than their male counterparts in times of hardships. Further, it is important to know

[1] SC/ST refers to Scheduled Caste and Scheduled Tribes. These are historically disadvantaged and marginalized sections of the Indian society. Social restrictions prevented them from having equal access to different facets of development, including health, education and nutrition. General-caste people are the ordinary people in India.

[19] Arc elasticity is defined as follows:

$$\left(\frac{Q_1 - Q_0}{\frac{Q_1+Q_0}{2}}\right) \div \left(\frac{p_1 - p_0}{\frac{p_1+p_0}{2}}\right),$$

where Q_0 is the initial quantity, Q_1 is the new quantity, p_0 is the initial price and p_1 is the new price. An arc price elasticity of -0.1 for a particular health care provider would mean that 10 percent increase in the price will lead to a 1 percent reduction in demand for that provider as indicated by the choice-relevant probability.

price-sensitivity of SC/ST versus general-caste people as SC/ST people are considered to be marginalized groups along with women and children in India.[20] The price elasticities for boys and girls are interesting in that for lower income groups (Q1 to Q3), boys' elasticities are generally higher for private hospital care in all the price ranges while girls' elasticities are higher for private doctors. However, the magnitudes of these differences in elasticities are very small. Increase in the price of health care by private doctors would reduce girls' demand for care from private doctors more than that of boys for all price ranges and for all income groups. Also arc price elasticity is generally more for an SC/ST child than for a general-caste child across all income groups and for all price ranges. This is true of all three providers. Thus if a child is SC/ST, her probability of health care usage diminishes more than her general-caste counterpart for a unit increase in the price of care. The price-sensitivity of demand for health care is very similar for both SC/ST and general-caste adult individuals.

Table 5 shows the elasticities of choice probabilities with respect to distance and other (choice-invariant) explanatory variables. When the government hospital is located at a distance between 2 - 5 kilometers, the probability of choosing government hospital by children decreases by 0.8 percent relative to private doctor, while the probability of visiting private hospital increases by 0.2 percent relative to private doctor. Similarly, when the government hospital is located at a distance more than 10 kilometer, the probability of a child visiting the government hospital reduces by 3.6 percent relative to private doctor while probability of visiting private hospital increases by 1.1 percent. For adults, attributes *DIST2* and *DIST3* have analogous interpretations of their respective elasticities. For *DIST4* of government hospital, however, the probability of choosing the government hospital increases by 5.9 percent relative to private doctor and probability of choosing private hospital reduces by 3.4 percent. Note that *DIST4* is a dummy indicating whether the government hospital is located at a distance more than 10 kilometers. Although it looks awkward at first glance, it might be a consequence of the way rural health infrastructure in India is organized. When someone has to travel more than 10 kilometers to a government health facility, it is very likely that such government facility is either a community health center (CHC) or some other government facility with better infrastructure. As discussed earlier, although sub-centers and primary health centers (PHC) in the rural areas are supposed to cater to the primary health care needs of the rural population, in reality, many of these are found to be non-functioning

[20] We have not reported the sex-wise and caste-wise arc elasticities of prices but have not reported to save space. They can be made availabe by the author on request.

either due to lack of medical personnel, medicines or large-scale absenteeism (Banerjee et al. (2003)). Thus people turn to community health centers (CHC) that are relatively better or other government or private hospitals that are well-equipped and provide better quality care. Such health facilities are expected to be located at distance more than 10 kilometers and this is why adults' probability of choosing government hospitals increases when the distance is more than 10 kilometers.

Having primary education or more increases the probability of a child visiting a government health facility by 0.9 percent relative to the private doctor and decreases her probability of visiting private hospital by 0.2 percent relative to private doctor. The analogous figures for adults are 0.3 percent and 0.1 percent respectively. If a child is SC/ST, she has 0.9 percent more probability of visiting government hospital relative to a private doctor while for SC/ST adults this figure is 0.6.

5. CONCLUSION AND FUTURE DIRECTION OF RESEARCH

Our study has found that both price and distance influence the choice of health care provider by an individual. It has also become clear from the estimates that women, children and SC/ST individuals are more vulnerable to price shocks in the health care sector than men, adults and general-caste population respectively. This suggests that the government might take up initiatives to promote better and easier access to care for these disadvantaged sections of the society. The fact that higher-income people are less sensitive to the price of health care can be used to impose some user fee where it is free or to increase the user fee where it is less in order to generate revenue. Government can use such extra revenue to increase the quality of health care provided through its network of rural health facilities. Such quality improvement would result in improved health outcomes as it is found that women and SC/ST population are more dependent on the government provision of health care than other providers. Since distance is an important determinant of health care provider choice, government can consider reaching out to the poor and the needy by revamping many of its dysfunctional health facilities in the rural areas.

The present framework does not allow us to have non-normal distributions for the random coefficients, which might sometimes be more realistic. This is a general drawback of the classical procedure, which can not handle highly non-quadratic log-likelihood surface (Train (2001)). An important way in which this research can be extended is to analyze the health care provider choice in a Bayesian framework as it allows more plausible distributions for the random taste coefficients.

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TABLE 1
Variable Definitions

VARIABLE DEFINITIONS	
GvtH	= 1 if the source of treatment is government hospital; = 0 otherwise;
PvtH	= 1 if the source of treatment is private hospital; = 0 otherwise;
PvtD	= 1 if the source of treatment is private doctor; = 0 otherwise;
P_j	Price of alternative j, where price includes total medical expenditure, transportation cost, cost on medical appliance, reimbursements and miscellaneous expenses, j = GvtH, PvtH, PvtD.
HHCEXPND	household's monthly consumption expenditure.
C_j	(HHCEXPND - P_j)$\forall$j = GvtH, PvtH, PvtD.
CSQ_j	$C_j^2\forall$j = GvtH, PvtH, PvtD.
DEAST	= 1 if individual belongs to Eastern India; = 0 otherwise;
DWEST	= 1 if individual belongs to Western India; = 0 otherwise;
DNORTH	= 1 if individual belongs to Northern India; = 0 otherwise;
DSOUTH	= 1 if individual belongs to Southern India; = 0 otherwise;
DUT	= 1 if individual belongs to a Union Territory; = 0 otherwise.
AGE	age in years.
AGE^2	age squared.
SEX	= 1 if female; = 0 if male.
SCST	= 1 if an individual is SC/ST; = 0 if otherwise.
BEDRIDDEN	= 1 if an individual confined to bed; = 0 otherwise.
TAKEREF	number of days treatment is taken within the reference period.
ADULT	= 1 if age $\geq$ 16; = 0 otherwise.
HHSIZE	household size.
ILLNU	number days the respondent reported ill
STATUS	= 1, if ailment started before the reference period and still continuing; = 2 if ailment started before the reference period and is over at the time of interview; = 3, if ailment started within the reference period and still continuing; = 4, if ailment started within the reference period and is over at the time of interview
HSTATUS	= 1 if (status = 1 or status = 3); = 0 if (status = 2 or status = 4).
EDU	= 1 if primary education or more; = 0 otherwise.
NOEDU	= 1 if no education; = 0 otherwise.
PRIEDU	= 1 if primary education; = 0 otherwise.
SECEDU	= 1 if secondary education; = 0 otherwise.
GRAEDU	= 1 if college education or more; = 0 otherwise.
DIST1$_j$	= 1 if 0 km < distance < 2 km; = 0 otherwise $\forall$ j = GvtH, PvtH, PvtD.
DIST2$_j$	= 1 if 2 km < distance < 5 km; = 0 otherwise $\forall$ j = GvtH, PvtH, PvtD.
DIST3$_j$	= 1 if 5 km < distance < 10 km; = 0 otherwise $\forall$ j = GvtH, PvtH, PvtD.
DIST4$_j$	= 1 if distance > 10 km; = 0 otherwise $\forall$ j = GvtH, PvtH, PvtD.
AWROAD	= 1 if all-weather road exists in the village; = 0 otherwise.
BUS	= 1 if buses run through the village; = 0 otherwise.

Note: C and C^2 are divided by 10^2 and 10^4 and age is divided by 10^2 for estimation.

TABLE 2
Descriptive Statistics

	Children				Adult			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
GvtH	0.22	0.41	0.00	1.00	0.21	0.41	0.00	1.00
PvtH	0.22	0.42	0.00	1.00	0.24	0.43	0.00	1.00
PvtD	0.56	0.50	0.00	1.00	0.55	0.50	0.00	1.00
P_GvtH	116.00	76.81	4.00	2480.00	138.61	80.57	7.00	2045.97
P_PvtH	137.20	88.52	13.00	1400.00	171.78	134.68	7.00	3042.75
P_PvtD	108.86	103.83	10.00	3350.00	146.48	130.30	10.00	2000.00
HHCEXPND	2187.99	1368.22	290.00	12970.00	2121.09	1354.02	159.00	12970.00
C_GvtH	20.72	13.64	2.14	128.29	19.82	13.47	0.41	128.05
C_PvtH	20.51	13.63	1.07	127.82	19.49	13.40	0.17	127.72
C_PvtD	20.79	13.62	1.00	120.45	19.75	13.44	0.78	128.45
CSQ_GvtH	615.39	1117.96	4.59	16457.98	574.47	1023.80	0.17	16395.96
CSQ_PvtH	606.29	1108.10	1.14	16338.05	559.60	1009.28	0.03	16311.13
CSQ_PvtD	617.74	1111.30	1.00	14508.20	570.44	1016.71	0.61	16499.40
DIST1_GvtH	0.41	0.49	0.00	1.00	0.39	0.49	0.00	1.00
DIST1_PvtH	0.11	0.31	0.00	1.00	0.10	0.30	0.00	1.00
DIST1_PvtD	0.45	0.50	0.00	1.00	0.44	0.50	0.00	1.00
DIST2_GvtH	0.28	0.45	0.00	1.00	0.29	0.46	0.00	1.00
DIST2_PvtH	0.14	0.35	0.00	1.00	0.15	0.35	0.00	1.00
DIST2_PvtD	0.23	0.42	0.00	1.00	0.24	0.43	0.00	1.00
DIST3_GvtH	0.19	0.39	0.00	1.00	0.20	0.40	0.00	1.00
DIST3_PvtH	0.23	0.42	0.00	1.00	0.22	0.41	0.00	1.00
DIST3_PvtD	0.17	0.38	0.00	1.00	0.17	0.37	0.00	1.00
DIST4_GvtH	0.12	0.32	0.00	1.00	0.12	0.32	0.00	1.00
DIST4_PvtH	0.52	0.50	0.00	1.00	0.54	0.50	0.00	1.00
DIST4_PvtD	0.15	0.35	0.00	1.00	0.15	0.36	0.00	1.00
AGE	5.39	4.76	0.00	16.00	42.42	17.53	17.00	99.00
AGE^2	5.17	6.96	0.00	25.60	21.07	16.61	2.89	98.01
EDU	0.30	0.46	0.00	1.00	0.32	0.47	0.00	1.00
NOEDU	0.58	0.49	0.00	1.00	0.57	0.50	0.00	1.00
PRIEDU	0.28	0.45	0.00	1.00	0.24	0.42	0.00	1.00
SECEDU	0.14	0.34	0.00	1.00	0.18	0.39	0.00	1.00
GRAEDU	0.00	0.06	0.00	1.00	0.01	0.11	0.00	1.00
HHSIZE	6.68	3.18	1.00	33.00	6.05	3.25	1.00	32.00
HSTATUS	0.27	0.45	0.00	1.00	0.35	0.48	0.00	1.00
SEX	0.44	0.50	0.00	1.00	0.53	0.50	0.00	1.00
SCST	0.33	0.47	0.00	1.00	0.33	0.47	0.00	1.00
ILLNU	5.63	3.28	1.00	15.00	6.85	4.05	1.00	15.00
BEDRIDDEN	0.45	0.50	0.00	1.00	0.50	0.50	0.00	1.00
TAKEREF	4.85	3.25	1.00	15.00	5.69	3.91	1.00	15.00
AWROAD	0.65	0.48	0.00	1.00	0.64	0.48	0.00	1.00
BUS	0.48	0.50	0.00	1.00	0.49	0.50	0.00	1.00

TABLE 3
Estimates under Multinomial and Mixed Logits

	Multinomial Logit				Mixed Logit			
	Children		Adult		Children		Adult	
Variables	GvtH	PvtH	GvtH	PvtH	GvtH	PvtH	GvtH	PvtH
DIST2	-0.37	-0.37	-0.44	-0.44	-0.54	-0.54	-0.81	-0.81
	(-5.05)*	(-5.05)*	(-6.13)*	(-6.13)*	(-3.58)*	(-3.58)*	(-4.56)*	(-4.56)*
DIST3	-0.74	-0.74	-0.71	-0.71	-0.91	-0.91	-1.09	-1.09
	(-9.23)*	(-9.23)*	(-9.22)*	(-9.22)*	(-5.68)*	(-5.68)*	(-5.98)*	(-5.98)*
DIST4	-1.00	-1.00	-1.01	-1.01	-1.58	-1.58	-1.55	-1.55
	(-12.57)*	(-12.57)*	(-13.23)*	(-13.23)*	(-8.09)*	(-8.09)*	(-7.88)*	(-7.88)*
C	0.35	0.35	0.12	0.12	0.38	0.38	0.12	0.12
	(4.87)*	(4.87)*	(2.66)	(2.66)	(7.25)*	(7.25)*	(3.12)*	(3.12)*
CSQ	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-2.46)	(-2.46)	(-0.71)	(-0.71)	(-3.73)*	(-3.73)*	(-0.95)	(-0.95)
A	-0.75	-0.18	-0.92	-0.10	-0.83	-0.15	-0.97	-0.02
	(-4.91)*	(-1.18)	(-5.06)*	(-0.60)	(-5.14)*	(-0.85)	(-5.08)*	(-0.11)
HHSIZE	-0.05	-0.05	-0.02	-0.05	-0.05	-0.06	-0.02	-0.05
	(-3.59)*	(-3.63)*	(-1.64)**	(-3.72)*	(-3.52)*	(-3.89)*	(-1.55)	(-3.74)*
ILLNU	-0.01	0.06	-0.01	0.06	-0.02	0.06	-0.02	0.06
	(-0.45)	(2.92)*	(-0.61)	(3.79)*	(-1.10)	(2.51)**	(-0.89)	(3.72)*
AGE	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00
	(1.51)	(1.17)	(1.36)	(1.14)	(1.22)	(1.10)	(1.32)	(0.46)
EDU	0.31	0.08	0.11	0.04	0.36	0.09	0.13	0.06
	(3.15)*	(0.80)	(1.08)	(0.37)	(3.53)*	(0.84)	(1.28)	(0.62)
SCST	0.36	0.05	0.25	0.18	0.37	0.02	0.26	0.19
	(3.98)*	(0.50)	(2.81)*	(2.02)**	(3.87)*	(0.15)	(2.85)*	(2.02)**
SEX	0.16	0.22	0.10	-0.02	0.17	0.25	0.10	0.00
	(1.84)**	(2.61)*	(1.15)	(-0.21)	(1.83)**	(2.66)*	(1.13)	(-0.02)
HSTATUS	-0.12	0.14	-0.10	0.19	-0.09	0.14	-0.08	0.09
	(-1.13)	(1.44)	(-1.05)	(2.11)**	(-0.79)	(1.22)	(-0.77)	(0.84)
TAKEREF	-0.03	-0.12	-0.02	-0.13	-0.02	-0.12	-0.02	-0.13
	(-1.28)	(-5.73)*	(-1.34)	(-7.95)*	(-0.88)	(-5.80)*	(-1.13)	(-8.17)*
Heterogeneity in Mean Parameters								
ILLNU	-	-	-	-	0.03	0.03	-	-
					(1.23)	(1.23)		
AGE	-	-	-	-	-		0.01	0.01
							(1.62)	(1.62)
HSTATUS	-	-	-	-	-		0.37	0.37
							(2.79)*	(2.79)*
Standard Deviation of Parameter Distributions								
sd_DIST2						0.01 (0.00)		0.06 (0.01)
sd_DIST3						0.03 (0.00)		0.07 (0.02)
sd_DIST4						1.80 (4.34)*		0.75 (1.43)
N		3756		3930		3756		3930
Log-lik		-3547		-3760		-3528		-3750
Adj. R^2		0.137		0.126		0.142		0.128

Notes: t-statistics in parentheses; *indicates significance at 1% level; ** indicates significance at 5% level.

TABLE 4
Arc Elasticities of Prices under Mixed Logit

Price Range	CHILDREN Q1	Q2	Q3	Q4	ADULT Q1	Q2	Q3	Q4
				Government Hospital (GvtH)				
0-50	-0.07	-0.06	-0.03	-0.01	-0.03	-0.02	-0.02	-0.01
50-100	-0.22	-0.18	-0.11	-0.02	-0.08	-0.07	-0.05	-0.02
100-200	-0.45	-0.38	-0.23	-0.04	-0.16	-0.14	-0.11	-0.05
200-500	-1.05	-0.92	-0.63	-0.13	-0.37	-0.33	-0.27	-0.12
				Private Hospital (PvtH)				
0-50	-0.07	-0.06	-0.04	-0.01	-0.03	-0.02	-0.02	-0.01
50-100	-0.23	-0.19	-0.11	-0.02	-0.08	-0.07	-0.05	-0.02
100-200	-0.46	-0.38	-0.24	-0.05	-0.15	-0.13	-0.11	-0.05
200-500	-1.05	-0.93	-0.66	-0.13	-0.37	-0.33	-0.27	-0.13
				Private Doctor (PvtD)				
0-50	-0.07	-0.04	-0.01	-0.00	-0.02	-0.01	-0.01	-0.00
50-100	-0.20	-0.13	-0.05	-0.00	-0.06	-0.04	-0.03	-0.01
100-200	-0.42	-0.27	-0.10	-0.01	-0.13	-0.09	-0.06	-0.02
200-500	-1.00	-0.76	-0.34	-0.03	-0.31	-0.23	-0.15	-0.04

Notes: Prices are in Indian Rupees at 1996 current prices; Q1 is the first income quartile, Q2 is the second income quartile and so on.

TABLE 5
Elasticities of Probabilities with respect to Explanatory Variables

Attributes		CHILDREN GvtH	PvtH	PvtD	ADULT GvtH	PvtH	PvtD
	GvtH	-0.08	0.01	0.05	-0.10	0.02	0.06
DIST2	PvtH	0.02	-0.04	0.04	0.02	-0.05	0.05
	PvtD	0.02	0.01	-0.04	0.03	0.02	-0.05
	GvtH	-0.11	0.04	0.07	-0.11	0.04	0.06
DIST3	PvtH	0.02	-0.13	0.06	0.02	-0.12	0.06
	PvtD	0.02	0.04	-0.06	0.03	0.04	-0.06
	GvtH	-0.36	0.19	0.22	0.59	-0.45	-0.07
DIST4	PvtH	0.11	-0.35	0.14	-0.34	0.54	-0.39
	PvtD	0.08	0.10	-0.20	-0.04	-0.19	0.23
	GvtH	-0.26	0.08		-0.10	0.07	
HHSIZE	PvtH	0.06	-0.29		0.02	-0.24	
	PvtD	0.07	0.08		0.03	0.07	
	GvtH	-0.10	-0.06		-0.09	-0.09	
ILLNU	PvtH	0.02	0.22		0.02	0.29	
	PvtD	0.03	-0.06		0.02	-0.09	
	GvtH	0.05	-0.01		0.12	-0.01	
AGE	PvtH	-0.01	0.04		-0.03	0.04	
	PvtD	-0.01	-0.01		-0.03	-0.01	
	GvtH	0.08	-0.01		0.03	0.00	
EDU	PvtH	-0.02	0.02		-0.01	0.01	
	PvtD	-0.03	-0.01		-0.01	0.00	
	GvtH	0.09	0.00		0.06	-0.02	
SCST	PvtH	-0.03	0.00		-0.02	0.04	
	PvtD	-0.03	0.00		-0.02	-0.02	
	GvtH	0.06	-0.02		0.04	0.00	
SEX	PvtH	-0.01	0.07		-0.01	0.00	
	PvtD	-0.02	-0.02		-0.01	0.00	
	GvtH	-0.02	-0.01		-0.02	-0.01	
HSTATUS	PvtH	0.00	0.03		0.01	0.02	
	PvtD	0.00	-0.01		0.01	-0.01	
	GvtH	-0.07	0.11		-0.09	0.15	
TAKEREF	PvtH	0.02	-0.43		0.02	-0.56	
	PvtD	0.02	0.11		0.02	0.15	