A Random Parameter Logit model for modeling Health Care Provider Choice in Bolivia

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ABSTRACT

In this paper we model health care provider choice in Bolivia with a Random Parameter Logit (RPL) using MECOVI data during the period 1999 and 2000. To our knowledge this is the first time that a RPL is used for modeling health care provider choice in Bolivia. We found that price and income are determinants of the decision choice of health care provider. Increasing government prices or fees shift the demand from government to private health facilities for children and women. In addition, women are more sensitive than children and adults to changes in price and income. The perception of Quality is significant just for private health facilities except for children. Finally, people would rather private instead of government facilities and self care treatment when they are ill.

JEL Codes: C01 C15 I38
Keywords: Random Parameter Logit, Government and Private Health Facilities, Quality, Prices or User Fees.

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I. INTRODUCTION

There are some people that believe that there might be a broken marriage between health economics – in particular, health care issues – and econometric techniques [18]. Nevertheless, health care demand modeling has undergone a major evolution since the early 1960's, when first economists became interested in estimating the demand for health services [30].

A specific study about health care has became interesting lately: Health Care Provider Choice. Choice behavior can be characterized by a decision process, which is informed by perceptions and beliefs based on available information, and influenced by affect, attitudes, motives and preferences; however, we can never measure all the aspects of the complex life course of consumer choices, so that we are never sure whether appears to be irrational behavior [4].

Modeling health care provider choice using different methodologies was being used including the use of Poisson [31], Tobit and Multinomial Logit [1] [5], Multinomial Probit [2] [5], Independent Multinomial Probit [5], Nested Multinomial Logit [9] [23], Conditional Logit or Heterogeneous Logit [16], Bayesian and Parametric [28], and Mixed Logit [6] models. In addition, some other papers combine the monetary and non monetary [13], [27], [29] aspects related to health care provider choice. However, just one [27] was related to Bolivia.

Bolivia, with its large indigenous population is poorly served by a hospital based health care system that ignores traditional cultures, in a country where more than 60 percent of the population is made up of indigenous people [8]. There are over 30 different cultural identities in Bolivia. The main ones are Aymara, Quechua and Guaraní nations, with their own knowledge, traditions and customs. In addition, Bolivia's social indicators demonstrate severe socioeconomic inequalities in the country where conditions of people living in rural areas, relative to those of the urban population have worsened in the last 15 years [26].

In this sense, it is important to develop more academic research related to health care demand in Bolivia in order to improve public policy. In particular we want to answer the following questions: Which are the determinants of health care provider choice in Bolivia during 1999 and 2000?, how much sensitive is people to changes in user fees or prices charged by health care facilities?, is important the perception of "quality" for government health care facilities?, which facility is preferred for people when they are ill?

In this paper we employ a Random Parameter Logit during 1999 and 2000 using a survey carried by the Bolivian Statistic National Institute (INE); specifically we use MECOVI (Continuous Household Survey).

The paper is composed as follows: second section discusses the model, third section describes the institutional framework and data description, fourth section describes the empirical results and the last section is conclusions.

II. THE MODEL

A version of demand for medical care model was first proposed by Gertler et al [13] in Peru. A similar model was used in Kenya by Mwabu et al [30]. Then other two models used a system of demand equations and a simultaneous-equation system was used by Akin et al [1] [2] respectively. Dor, Gertler and Van der Gaag [9] used a reduced form model of the utility from quality. However, none of them used a Random Parameter Logit (RPL) but Borah [6] in a study of choice provider in rural India.

In order to use a RPL model, we must set up the economic model framework. The model uses a direct and indirect utility functions for those individuals who were sick and had to choose between medical providers. In essence, individuals are faced with a discrete choice decision – each of which has a different potential impact (efficacy) on their health [13] –, so that a decision must be made among the various provider alternatives, including self care.

The benefit from consuming medical care is an improvement in health and the cost of medical care is a reduction in the consumption of other goods. Furthermore, the patient is assumed to choose the health care alternative that yields the maximum expected utility[1]. Let the utility function be:

(1) $U_{ij} = U(C_{ij}, H_{ij})$

There are *i* individuals facing *j* alternatives, where $j \in n, n = \{1,2,...,N\}$, U_{ij} is the direct conditional utility that individual *i* expects from provider *j*, C_{ij} is the individuals' level of consumption other than medical expenses and H_{ij} is the expected level of improvement in health after receiving a treatment given an election

[1] However, sometimes health professionals limit the actual choices patients can make by the treatments they offer to patients in hospitals, outpatient treatments, nursing homes, hospice and other clinical settings [20].

of medical provider. We can assume that the utility function is stable in time and does not change with new information. The usual assumptions about the utility function apply here: $U_C > 0, U_{CC} < 0$ and $U_H > 0, U_{HH} < 0$

Medical care demand depends on both observed and unobserved characteristics of the individual seeking medical care and the provider. The individual's observed characteristics – that may influence the final choosing – might be sex, age, education, income, etc.; the unobserved could be the perception of the quality and service of the provider, preference for certain medical procedures or just a preference for being treated in certain way. The provider's observed attributes may be the user fees charged, quality of the service[2] – measured as availability of drugs and post natal medical services –, the distance from the ill person to the provider's center and waiting times for getting medical attention; while unobserved would include the reputation of the provider, the level of cleanliness of the medical center, the provider's medical experience, etc. In this sense we can define:

$$(2)\quad C_{ij} = Y_i - p_{ij}$$

$$(3)\quad \ell\eta\ h_{ij} = \theta_j + \varpi\ X_{ij} + \varepsilon_{ij} \quad where\ H_{ij} = \ell\eta\ h_{ij}$$

In equation (2) the individual's consumption is a function of the monthly income Y_i and the expenses incurred in order to obtain medical attention p_{ij} – such as medical services for all the visits, drugs and other expenses –. The relation of price and income is important because if the price effect were independent of income, this will lead us to a restrictive assumption [9].

In equation (3) we can model in a log-linear form, the consumer's valuation of some provider's unobserved attributes θ_j, and observed attributes X_{ij} of provider *j* – which enters the model as interactions with observed individual characteristics – ; where h_{ij} is the medical care that an individual *i* receives from a provider *j* and it is assumed to be positive. In addition, the coefficient vector ϖ has components that are either random or fixed. A random coefficient[3] represents random taste of

[2] There are many ways of measure quality such as: physical facilities, number of staff members and level of supervision, availability of essential drugs and equipment, provision of basic health services, infrastructure (electricity and running water) and basic adult and child health services including: availability of a laboratory and the ability to vaccinate children and to provide prenatal, postnatal services, and number of functioning X-ray machines [24]. However, due to data limitations we just use availability of essential drugs and postnatal services as a proxy of quality. In this way we are assuring the eternal critics about lacking to measure and post incorporation of quality in this kind of studies [2] [9] [16].

[3] This can be represented as random tastes heterogeneity and can be decomposed into observed and unobserved (random) components [6].

individual i for an observed attribute, say x_{ij} of the provider j or interaction of some individual characteristics (e.g. age, sex, etc.) with the provider attribute x_{ij}. Since we are modeling (3) in a log-linear way, this guarantees non-negative values for the random coefficients, whereas the other three (normal, triangular and uniform) almost certainly guarantee some negative values [14]. Finally, the individual's unobserved attributes are incorporated in ε_{ij}. In this way, all the observed and unobserved attributes are specified. An interesting feature is that the income is interacting with prices in equation (2) in order to determine whether low income individuals are price sensitive [2] [13].

Together, equations (1), (2) and (3) determine a general structural specification of a behavioral model of health care demand. In order to implement this model we must choose a functional form. Gertler and Van der Gaag [11] and Gertler et al [13] had demonstrated that the utility function described in equation (1) is linear in health status and quadratic in consumption:

(4) $U_{ij} = \alpha_{i0} H_{ij} + \alpha_{i1} C_{ij} + \alpha_{i2} C_{ij}^2 + \xi_{ij}$

and should allow for a non-constant marginal rate of substitution of health for consumption. If we replace H_{ij} from (3) into equation (4) and normalized $\alpha_{i0}=1$ then we will have our indirect utility function:

(5) $U_{ij} = \theta_j + \boldsymbol{\beta}_i \ \boldsymbol{X}_{ij} + v_{ij}$

where $\boldsymbol{\beta}_i = (\varpi, \alpha_{i1}, \alpha_{i2})$, $\boldsymbol{X}_{ij} = (X_{ij}, C_{ij}, C_{ij}^2)$, $v_{ij} = (\varepsilon_{ij}, \xi_{ij})$ (stochastic component) and θ_j is defined as above. Thus, any individual knows her $\boldsymbol{X}_{ij}$ and chooses to attend a health care provider when she was ill. However, θ_j and $\boldsymbol{\beta}_i$ remain unidentified and must be estimated. For purposes of estimation, U_{ij} remains latent and a function such y_{it} acquires the values of 1 if the individual makes a health care provider choice and 0 otherwise. Thus, the probability that an individual i choose alternative j is given by:

(6) $P(y_{ij} | \boldsymbol{\beta}_i, \boldsymbol{X}_i) = \prod_{j \in n} P_{ij}^{y_{ij}}$

We want to allow for the possibility that the information relevant to making a choice that is unobserved may indeed be sufficiently rich in reality to induce correlation across alternatives in each choice situation and indeed across choice situations [14]. In this context, we split the stochastic component v_{ij} into two additive components $\varepsilon_{ij}, \xi_{ij}$. Further, ξ_{ij} is a random term with zero mean whose distribution over individuals depends in general on observed attributes relating to provider *j* and individual *i* and ε_{ij} is a random term with zero mean that is iid over alternatives and does not depend on observed attributes. Denote the density of ξ_{ij} by $f(\xi_{ij} | \Psi)$ where Ψ are the fixed parameters of the distribution. For a given value of ξ_{ij}, the conditional choice probability that individual *i* chooses alternative *j* is:

$$(7)\quad P(j | \xi_{ij}) = \frac{\exp(\theta_j + \beta_i X_{ij})}{\sum_{j-1}^{n} (\theta_j + \beta_i X_{ij})}$$

Since ξ_{ij} is not given the (unconditional) choice probability is the following Logit integrated formula integrated over all values of ξ_{ij} weighted by the density of ξ_{ij}:

$$(8)\quad P_{ij} = \int_{\xi_i} P(j | \xi_{ij}) f(\xi_i | \Psi) dF_{\xi}$$

This is called the Random Parameter Logit model.

Random Parameter Logit

A common concern about discrete choice models is the Independence of Irrelevant Alternatives (IIA) which is the ratio of probabilities of choosing any two alternatives that must be independent of the attribute or the availability of a third alternative [15]. With the RPL model through the relaxation of the IIA property enable the model to be specified in such a way that the choice sets can be correlated across each individual [14]. The same happens with the Multinomial Probit, which allows all possible correlations among error terms [2], [10], [21]. Nevertheless, the normal distribution with the latter model may not be appropriate in all situations [6]. In addition, the main impediment to widespread use of the Multinomial Probit is that the estimation of the choice probabilities is very cumbersome and time consuming [5].

On the other hand with Multinomial Logit the assumption is that the correlation between each pairing of the errors in the model is zero, restricting the correlation just for pairs [2], [17]. What is more, according to Bolduc [5], it may be inappropriate to formulate policy recommendations based on this model, which is by far the most widely used estimator in the literature.

The RPL model provides greater flexibility compared to other discrete choice models in that the random components of the utility specification may be assumed to have any distribution, so that this allows flexible modeling of unobserved heterogeneity that results from unobserved factors such as tastes and attitudes, waiting times, etc. [6]. Thus, the RPL model is considered to be the most available promising state of the art discrete choice model currently available [6].

III. Institutional Framework and Data Description

MECOVI Survey

The MECOVI (Continuous Household Survey) is a sample investigation carried out to particular household. It has done through a multi-thematic questionnaire, which allows the study of life conditions of household and their different components.

The MECOVI's aim is the empowerment and institutionalization of household surveys that measure life conditions. The questionnaire is organized by sections and allows the investigation of general characteristics, educational, labor, health, expenses, income, and basic services of household.

The analysis unities for this paper were: 1) household as a consumption unity, where took place income and expenses transactions; and 2) the household members looking for socio-demographic characteristics, labor, and income.

The survey contains information about established household in capital cities, urban areas and rural areas of Bolivia. The capital cities and metropolitan area composed by Sucre, La Paz, El Alto, Cochabamba, Oruro, Potosí, Tarija, Santa Cruz, Trinidad and Cobija.

The sample design for the survey contained the selection of a primary unities samples (UPM's) that correspond to 130 household (Census Sector). In the other hand, in the disperse area the UPM's are communities with different household sizes that correspond to 50 household approximately. Finally, the secondary unities samples (USM's) are particular household within the selected UPM.

Health Care System of Bolivia

In Bolivia Health Care is delivered through the Ministry of Health, the Social Security Fund and the Private Sector. The Ministry of Health is responsible for the health care of the poor and covers only 25% of the population. The Social Security Fund serves industrial workers, civil servants and a small percentage of the service sector, which is 20% of the population. The Private for-profit sector provides services to about 5% of the population, and the non-profit sector (NGO's) 10% of urban dwellers and 25% of the rural population. An estimated 30% of the population does not receive western medical care. Some of these people consult traditional healers known as yatiris, jampiris, curanderos, cullahuayas and naturistas [19]. In addition, Considering the Bolivia's total population, the number of beds in Medical Establishments is not enough. This is due because of infrastructure and reduced personnel they have [7].

Finally, the expenditures for health by government are not considerable. As a result, there are not enough Medical Establishments, the number of beds is insufficient, and the number of medical trained professionals is insufficient. In addition, the national expenditure in health per capita is too low. All these factors seem to lead to inefficiency and not enough service for most of Medical Establishments in Bolivia [7].

Data Description

In order to model health care provider in Bolivia, we should focus just in patients that are considered ill or had some illness during the period of MECOVI survey. In addition, this paper only covers outpatient treatment because of the nature of data.

For purposes of estimation, the data corresponds to 1999 and 2000. Both databases were merged and individuals from 1999 that were interviewed in 2000 were eliminated. Thus, the data contains 1999 individuals and new data added for 2000. Additionally, three RPL models were designed: one for children under 5 years old, for adults, and for women who had a child twelve months before the survey.

In order to modeling equation (5) we used the following variables:

TABLE 1. VARIABLE DESCRIPTION

Variable	Description
Latent Utility Variables	
Gov_{ij} a), b), c), d)	= 1 if the source of treatment is a Government health center; = 0 otherwise.
$Priv_{ij}$ a), b), c), d)	= 1 if the source of treatment is a Private health center; = 0 otherwise.
$Self_{ij}$ a), b), c), d)	= 1 if the source of treatment is Self Care; = 0 otherwise.
Provider's Observed Attributes and Interactions with Individual's Observed Characteristics	
$Quality_j$ a), b), c)	= 1 if essential drugs and post natal services were available at health center *j*; = 0 otherwise
P_j a), b), c), d)	Price of alternative *j*
$Priv_j\_Inc_i$ a), b), c)	Source of treatment *Private* interacted with *Income*. $Gov_j\_Inc_i$ and $Self_j\_Inc_i$ are defined similarly.
$Priv_j\_Age_i$ a), b), c)	Source of treatment *Private* interacted with Age_i. $Gov_j\_Age_i$ and $Self_j\_Age_i$ are defined similarly.
$P_j\_Gender_i$ a), b)	*Price* of alternative *j* interacted with Gender.
$Qua_j\_Inc_i$ a), b), c)	*Quality* of health center *j* interacted with *Income*.
Individual's Observed Characteristics	
$Cond_i$ a), b), c)	= 1 if individual was ill or had an illness during or before the survey; = 0 otherwise
$Education_i$ a), b), c), e)	= 1 if education up to primary level completed and capable of reading & writing; = 0 otherwise
$Gender_i$ a), b), c)	= 1 if male; = 0 otherwise
Age_i a), b), c)	Expressed in years
$Area_i$ a), b), c), d)	= 1 if urban; = 0 otherwise
$Income_i$ a), b), c), e), f)	Income per Household Head expressed in Bolivianos, measured monthly.
$Cons_i$ a), b), c), e), g)	Household's Consumption expressed in Bolivianos
$Cons2_i$ a), b), c)	Household's Consumption squared expressed in Bolivianos
EDA_i a)	= 1 if individual had diarrhea; = 0 otherwise.
IRA_i a)	= 1 if individual had bronchopneumonia or pulmonary tuberculosis; = 0 otherwise.

a) Used for children under 5 years old RPL model
b) Used for adults RPL model
c) Used for women RPL model who had a child twelve months before the survey
d) Used for imputation of prices
e) Used as a proxy from Household Heads as a proxy for their children.
f) Includes main activity labor income, secondary activity labor income, extra hours labor income, bonus labor income, and non labor income.
g) Includes education expenditures and consumption other than medical expenditures.

Unlike other studies we incorporated essential drugs and post natal services as a proxy for Quality within provider's observed attributes.

In order to estimate the RPL model we need all the alternative prices P_j of alternative health care providers that were not chosen for individuals when they were ill [6], [13], [23]. The methods for imputing the missing prices include algorithms using separate pricing equations for each provider [6], hedonic price equations and corrections for possible bias [13] and random draws with replacement [23].

The expected amount spent by a person for a specific illness may depend not only on the standard fees, but also, for example, on the type of treatment, quality of treatment, individual idiosyncratic elements, and other non-medical expenses chosen by the patient [23].

For estimating the prices, first we gathered all individuals in groups according to the source of treatment chosen, type of illness and treatment, city, area (urban or rural) and finally UPM. In this way we assure homogeneity for estimating the alternative prices or user fees. Then, since the groups were similar, we started to estimate the prices according to Medical User Fees Reference Book [25] used for all doctors (public and private) as a reference in all health centers around Bolivia. In this book all the user fees are expressed as non monetary unities each of them equal to 10 bolivianos.

The interacted variables were added in order to capture the sensitiveness of gender with the prices, quality with income and health center facility with income and age respectively. The observed individual's characteristics such as education, gender, age, income, etc. assure the incorporation of provider's observed attributes, interactions with individual's observed characteristics X_{ij} in equation (5). Together X_{ij} with the consumption level C_{ij}, C_{ij}^2 gives us the vector $\tilde{X}_{ij} = (X_{ij}, C_{ij}, C_{ij}^2)$

The dependent variables include various alternatives for an ill individual: 1) Public Hospital, 2) Health Center, 3) Health Post, 4) National Health System Centers, 5) Private Clinic/Hospital, 6) Private Medical Office, 7) Pharmacy and 8) Home. Thus, options 1) – 4) were classified as Gov_{ij}, 5) – 7) as $Priv_{ij}$ and 8) as $Self_{ij}$.

It is worthy to mention that many studies about health care provider choice include distance as provider's observed attribute [2], [6], [30]; others considered waiting times [9] and travel times [1], [13]; however, for this study we do not have this variable. What is more, due to the typography and complexity of Bolivia is very difficult to measure distance to a health center provider.

Finally, for both consumption and income variables only positive values greater than zero were considered in order to avoid for unrealistic values.

TABLE 2. DESCRIPTIVE STATISTICS

	CHILDREN (n=980)				ADULT (n=1031)				WOMEN (n=120)			
	MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX
Gov	0.4	0.5	0.0	1.0	0.4	0.5	0.0	1.0	0.5	0.5	0.0	1.0
Priv	0.1	0.3	0.0	1.0	0.1	0.3	0.0	1.0	0.5	0.5	0.0	1.0
Self	0.4	0.5	0.0	1.0	0.3	0.5	0.0	1.0	0.0	0.1	0.0	1.0
P_Gov	12.3	42.8	0.0	600.0	71.8	386.6	0.0	7500.0	83.4	328.4	0.0	3000.0
P_Priv	7.0	44.8	0.0	800.0	41.9	325.7	0.0	7800.0	95.4	411.4	0.0	3100.0
P_Self	4.0	17.9	0.0	300.0	6.3	45.3	0.0	1300.0	0.3	4.1	0.0	60.0
Qual_Gov	0.3	0.5	0.0	1.0	0.4	0.5	0.0	1.0	0.5	0.5	0.0	1.0
Qual_Priv	0.1	0.3	0.0	1.0	0.1	0.3	0.0	1.0	0.5	0.5	0.0	1.0
Qual_Self	0.3	0.4	0.0	1.0	0.3	0.5	0.0	1.0	0.0	0.1	0.0	1.0
Inc*Gov	421.1	1038.8	0.0	9570.0	214.0	999.6	0.0	32000.0	229.3	1743.7	0.0	32000.0
Inc*Priv	175.4	959.4	0.0	17823.3	131.7	854.8	0.0	20166.7	133.1	594.8	0.0	6416.7
Inc*Pself	405.4	1272.1	0.0	15000.0	104.1	528.3	0.0	12250.0	8.7	161.8	0.0	3045.0
Age*Gov	0.8	1.3	0.0	4.0	15.7	24.1	0.0	90.0	13.8	14.5	0.0	49.0
Age*Priv	0.2	0.8	0.0	4.0	4.7	14.5	0.0	87.0	13.6	15.0	0.0	47.0
Age*Self	0.9	1.4	0.0	4.0	12.5	21.3	0.0	90.0	0.4	3.8	0.0	41.0
P*Gender_Gov	6.4	30.7	0.0	500.0	38.9	319.8	0.0	7500.0	-	-	-	-
P*Gender_Priv	3.7	29.3	0.0	700.0	21.3	229.7	0.0	6000.0	-	-	-	-
P*Gender_Self	2.6	16.8	0.0	300.0	3.1	28.2	0.0	850.0				
Qual*Inc_Gov	327.7	916.1	0.0	8741.3	214.0	999.6	0.0	32000.0	229.3	1743.7	0.0	32000.0
Qual*Inc_Priv	156.2	948.3	0.0	17823.3	131.7	854.8	0.0	20166.7	130.6	593.7	0.0	6416.7
Qual*Inc_Self	300.0	1145.7	0.0	15000.0	104.1	528.3	0.0	12250.0	8.7	161.8	0.0	3045.0
Education	0.9	0.2	0.0	1.0	0.9	0.5	0.0	1.0	0.1	0.2	0.0	1.0
Gender	0.5	0.5	0.0	1.0	0.5	0.5	0.0	1.0	-	-	-	-
Age	2.0	1.4	0.0	4.0	38.5	21.5	6.0	98.0	27.8	7.2	14.0	49.0
Area	0.4	0.5	0.0	1.0	0.5	0.5	0.0	1.0	0.5	0.5	0.0	1.0
Income	1132.5	1771.6	4.2	17823.3	948.6	1799.5	0.8	32000.0	1010.4	2919.7	5.0	32000.0
Cons	100.6	220.8	1.0	2826.7	86.0	145.7	1.0	1420.0	50.7	82.6	1.0	550.0
Cons2	36431.3	387977.3	0.0	7990044.4	16392.5	91424.0	0.0	2016400.0	4146.0	23906.2	0.0	302500.0
EDA	0.5	0.5	0.0	1.0	-	-	-	-	-	-	-	-
IRA	0.8	0.4	0.0	1.0	-	-	-	-	-	-	-	-

IV. EMPIRICAL RESULTS

RPL MODEL FINDINGS

In order to estimate the model the Broyden algorithm and LIMDEP software were used. We estimated three models described in the previous section. The RPL models were estimated using Gov_{ij} and $Priv_{ij}$ compared to $Self_{ij}$. Therefore, the estimated coefficients must be interpreted with relation to $Self_{ij}$. The number of draws required to secure a stable set of parameter estimates varies enormously; the best test is to always estimate models over a range of draws. [14] In our models 500 draws were used. The results are described in Table 3.

TABLE 3. RANDOM PARAMETER LOGIT ESTIMATES

	Children		Adults		Women	
	Gov	***Priv***	***Gov***	***Priv***	***Gov***	***Priv***
CONS	0.00541 ***	0.01122 ***	0.00922 ***	0.00990 ***	0.01738 ***	0.01944 ***
	0.00005	0.00013	0.00007	0.00009	0.00055	0.00116
CONS2	0.00000 ***	-0.00001 ***	-0.00001 ***	-0.00001 ***	-0.00002 ***	-0.00003 ***
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
GENDER	0.05425 ***	0.04195 ***	0.05065 ***	0.09912 ***	-	-
	0.01159	0.01578	0.01272	0.01476	-	-
AGE	-0.02505 ***	-0.00351	-0.00389 ***	-0.00305 ***	-0.00647 ***	-0.00311
	0.00427	0.00538	0.00043	0.00048	0.00362	0.00677
EDUCATION	0.22623 ***	-0.01268	0.05828 ***	-0.01067	0.03941	0.47935 **
	0.04330	0.06027	0.01666	0.02002	0.09912	0.18656
QUALITY	-0.02295	-0.11578 ***	-0.09800 ***	0.10006 ***	0.10734	2.46818 *
	0.02456	0.03196	0.03731	0.03334	0.22564	1.37990
EDA	0.04762 ***	0.06378 ***	-	-	-	-
	0.01740	0.02214	-	-	-	-
IRA	0.17585 ***	-0.02380	-	-	-	-
	0.01890	0.02487	-	-	-	-
AREA	0.01570	0.11671 ***	0.14574 ***	0.02615	0.25236 **	0.70579 ***
	0.03760	0.04396	0.04070	0.04111	0.11051	0.14365
INC*_S¥	0.00000	0.00003 ***	0.00001 ***	0.00004 ***	0.00009 ***	0.00292
	0.00000	0.00001	0.00000	0.00000	0.00003	0.00178
AGE*_S¥	0.03034 ***	0.01898 **	0.00035	0.00001	-0.00689 ***	-0.00230
	0.00589	0.00907	0.00035	0.00042	0.00215	0.00358
P*GENDER_S¥	-0.00033 *	-0.00017	-0.00007 ***	-0.00005 ***	-	-
	0.00017	0.00015	0.00002	0.00001	-	-
QUA*INC_S¥	0.00003 ***	-0.00001 **	fixed	-0.00003 ***	fixed	-0.00287
	0.00000	0.00000	-	0.00000	-	0.00178
N	576.00	404.00	592.00	439.00	65.00	55.00
Log likelihood	-67988.03	-44649.00	-69352.00	-57135.00	-5393.00	-2590.00
R-sqrd	0.19	0.28	0.32	0.33	0.38	0.35
RsqAdj	0.17	0.25	0.30	0.31	0.30	0.02

Notes: ¥ _S denotes interaction with the health facility: *Gov_{ij} or $Priv_{ij}$* depending on the dependent variable.
* Indicates significance at 10%
** Indicates significance at 5%
*** Indicates significance at 1%
Standard errors in parenthesis

Most of the literature on health care provider choice has been restricted to a situation in which the choice set is fixed across individuals [23]. In this paper, specifically in MECOVI survey the true generating process may vary across individuals by geographical location (cities, urban – rural, UPM's and USM's), nature of illness (EDA, IRA) and affordability. Moreover, identification of a discrete choice model requires variation across alternatives. Although variation across individuals (such as demographic variables) is not necessary it is desirable to include them in order to obtain precise estimates [13], [23].

The first interesting result is that Consumption is significant for all groups (children, adults and women) suggesting that price and income are determinants of the decision choice of health care provider according to equation (2). This result is in concordance with previous studies [13], [6], [9], [23]. However, income and price do not enter the model directly, so that elasticities between both variables might be estimated [13]. Consumption squared is also significant and has the expected sign suggesting that the utility function is concave in consumption, situation described in section II.

Older individuals in all groups have a preference for self care treatment instead of government and private health centers and doctors since age is negative and significant for *Gov* regressions. A similar situation happens just for adults in *Priv* regression.

More educated parents and individuals would rather government facilities when they are ill instead of treating by themselves.[4] This is true for the benefits for children under 5 years old prevailing in government health facilities since almost all the medicines, drugs, and user fees are free due to SUMI (Universal Secure Maternal Infantile) system. This advantage is also reflected in specific ill-types for children such as diarrhea (EDA) or bronchopneumonia or pulmonary tuberculosis (IDA), where government are preferred instead of private facilities and/or self care treatment. Thus, health information is valuable to the consumer because it allows her to make better decisions about medical care [22]. However, for women that had a child before the survey, have completed up to primary level and live in an urban area;[5] prefer a private facility health center instead of self care. This is linked with the fact that medical auxiliaries are concentrated more in rural areas instead of doctors and nurses. Furthermore, the health sector does not have enough medical trained professionals in rural areas, decreasing the quality of medical attention [7].

The perception of Quality – measured as the availability of essential drugs for medication and post natal services – is significant just for private health facilities except for children group. People would rather private instead of government facilities and self care treatment when they are ill. This fact might be true because there has not been an increase in the number of General Hospitals from 1999 to 2003. This might be "a priori" indicator that expenditure in Investment has not done; consequently, the services (including drugs) cannot be enhancing in order to cover more population seeking for medical attention. [7]

[4] Information increases the probability that a consumer uses medical care. What is more, poorly informed consumers tend to underestimate the productivity of medical care in treating illness [22].

[5] Different arguments have been suggested for a positive relationship between health care expenditure and urbanization [12].

If income INC*S_ were the only determinant when choosing a health care provider, parents and individuals will chose a private health center instead a government or self care treatment. This is related with provider's quality perceived by individuals interacted with income QUA*INC_S. Nevertheless, the negative sign of the latter variable might suggest that the user fees charged are high.

Eventually, an individual's decision to seek or purchase medical care is more likely to be based on individual characteristics such as the number of unhealthy days rather than prices, costs of medication, etc. [3]

POLICY AND SIMULATIONS ON RPL MODELS

Since is difficult to compare magnitudes of coefficients directly in RPL estimation results, a simulation based on some scenarios were done [2].

a) Increasing Government prices or fees in 10%.
b) Increasing household income by 20%.
c) Increasing household consumption (other than medical expenses) by 10%

The procedure was to take the actual values of the independent variables for each individual and compute the probability of use for Gov_{ij} and $Priv_{ij}$ holding constant $Self_{ij}$. These probabilities were then averaged over the sample to obtain the results in Table 4. Then we changed the variables described in points a), b) and c) holding the rest constant. We repeated the exercise with the two health care provider choices.

TABLE 4. POLICY SIMULATIONS FOR RPL MODELS

			Gov	Priv		Gov	Priv		Gov	Priv
CHILDREN		*Actual Prob.*	0.4030	0.3786		0.4030	0.3786		0.4030	0.3786
		New Prob.	0.3921	0.3985		0.3912	0.3988		0.3922	0.3985
		Absolute Δ	-0.0109	0.0199		-0.0118	0.0202		-0.0108	0.0199
		Relative Δ %	-2.70%	5.26%		-2.93%	5.34%		-2.68%	5.26%
ADULT	a)	*Actual Prob.*	0.3578	0.3418	b)	0.3578	0.3418	c)	0.3578	0.3418
		New Prob.	0.3713	0.3847		0.3800	0.2930		0.3985	0.3414
		Absolute Δ	0.0135	0.0429		0.0222	-0.0488		0.0407	-0.0004
		Relative Δ %	3.77%	12.55%		6.20%	-14.28%		11.38%	-0.12%
WOMEN		*Actual Prob.*	0.3348	0.2245		0.3348	0.2245		0.3348	0.2245
		New Prob.	0.2923	0.3221		0.2903	0.3173		0.2994	0.3224
		Absolute Δ	-0.0425	0.0976		-0.0445	0.0928		-0.0354	0.0979
		Relative Δ %	-12.69%	43.47%		-13.29%	41.34%		-10.57%	43.61%

Given an increase in prices or user fees in government health facilities (policy a)) the predicted probabilities of use are reduced for both children and women, except for adults that is the opposite. The reduction is more perceptible in women (12.69%). Thus, the probability of use Private facilities is increases for all groups. The strongest one is for women (43.47%). It is interesting that for children the probability of use is reduced since actually all prices or user fees are free. Hence, women and children seem to be sensitive – more in the women's case – than adults group to a change in Government health facilities user fees.

The second scenario b) increases the probability of use for government health facilities just for adults (6.20%). Children and women prefer to use a private facility given an increase in household incomes by 20%. These findings for women are similar to those in previous section. Women have a preference to pay more, increasing their probability (41.34%) of use, for a better medical attention – especially post natal services – for their children. Therefore, an increase in household income will have a negative effect for government facilities suggesting two issues: there must be a decrease in the prices or user fees charged and/or an improvement in the provider's quality perceived by individuals.

Finally, for scenario c) children and women would rather use private facilities given an increase in household consumption. With this policy there is a trade off between choosing a government or private facility having less monetary income (due the consumption increase). Thus children and women are able to sacrifice more income for a better medical attention supplied by private facilities.

ELASTICITIES

In order to observe the impact of prices and income in our RPL model, arc price and arc income elasticities were estimated. The arc elasticity is defined as $E = \frac{\Delta P}{\overline{P}} \Big/ \frac{\Delta \Phi}{\overline{\Phi}}$ where P reflects the probability of use for a certain facility health, $\overline{P}$ is the average of the probabilities, and Φ reflects any variable such as price or income. The elasticities measure the sensitivity of demand (probability of use) for each type of facility to a change in price or income. Thus, we estimated the probabilities of use for Gov_{ij} and $Priv_{ij}$ holding constant $Self_{ij}$ following the same procedure described above. The variables that we changed were the price or user fee for government facilities and income. Hence, the elasticities were estimated with respect to those changes. Results are described in Table 5.

TABLE 5. ARC ELASTICITIES OF DEMAND

	With respect to…	***Gov***	***Priv***
CHILDREN	Gov Price fee	-0.2882	-0.0677
	Income	-0.1634	0.2858
ADULT	Gov Price fee	0.4386	0.6191
	Income	0.3310	-0.8456
WOMEN	Gov Price fee	-1.4445	0.6223
	Income	-0.7830	1.8841

A 10% increase in the government fees will reduce in 2.88% and 0.67% the demand for government and private health facilities for children respectively. In contrast, for adults a 10% increase in government fees will increase the demand in 4.39% and 6.19% respectively. Women have a quite elastic demand, since the increase in fees will reduce demand for government facilities in 14.45% and will increase for private in 6.22%. Again we observe that increasing the government fees will shift the demand from government to private health facilities for children and women. Adults seem to be price inelastic to the increase; however, the increase for using private (6.19%) is higher than for government facilities (4.39%).

For income changes, women result to be price elastic also. Given a 10% increase in income women will increase the use of private facilities by 18.84%. Thus, health is considered a normal good since a rise in income increases the probability that children and women purchase "higher price/higher quality" alternatives [13].

V. CONCLUSIONS

In this paper we model health care provider choice in Bolivia with a Random Parameter Logit (RPL) using MECOVI data during the period 1999 and 2000. To our knowledge this is the first time that a RPL model is used for modeling health care provider choice for Bolivia.

We found initially that price and income are determinants of the decision choice of health care provider;[6] however price and income do not enter in the model directly. By estimating elasticities we discovered that increasing government prices or fees shift the demand from government to private health facilities for children and women; the preference for private facilities is stronger for women in relation to the other groups. In addition, women are more sensitive than children and adults to changes in price and income. On the other hand, an increase in household incomes will have a negative effect for government facilities suggesting two issues: there must

[6] Similar findings were found in previous studies [23], [27] and [29].

be a decrease in the prices or user fees charged and/or an improvement in the provider's quality perceived by individuals.

The perception of Quality – measured as the availability of essential drugs for medication and post natal services – is significant just for private health facilities except for children group. People would rather private instead of government facilities and self care treatment when they are ill.

Education plays an important role. More educated parents and individuals would rather government facilities when they are ill instead of treating by themselves. This must be complemented with information about the benefits government facilities offer. However, most of the analysis we have done in this paper suggest that Government facilities lack of quality. In this sense, policy issues for demand analysis, in a low income country such as Bolivia, are access to facilities, capturing true demand patterns, and demand creation or how to assure that new government services are used [1].

To sum up, according to Canaviri [7] the expenditures for health by government are not considerable. As a result, there are not enough Medical Establishments, the number of beds is insufficient, and the number of medical trained professionals is insufficient. In addition, the national expenditure in health per capita is too low. All these factors seem to lead to inefficiency and not enough services for most of Medical Establishments in Bolivia. Factors that shift the potential demand that government "may" have to private health facilities or simply self care treatment.

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