CHAPTER: V

Factors Influencing Health Care Utilization Behavior of the People of Rural Goalpara: an Econometric Analysis

CHAPTER: V

Factors Influencing Health Care Utilization Behavior of the People of Rural Goalpara: an Econometric Analysis

5.1 Introduction

In Chapter 4, it has been shown how various economic and non-economic factors influence patients' health care utilization for both in-patient and out-patient treatment in terms of simple percentage in study area. To have a deeper understanding about how the various economic and non-economic factors affect in-patient and out-patient health care, econometric analysis is required now. So, to study about the health care utilization behavior among the people in the study area, econometric analysis have been done in terms of logistic regression model for in-patient health care and multinomial logit model for out-patient health care in this chapter.

The outline of the chapter is as follows. In section 5.2, based on the existing literature, relevant model has been developed for studying the in-patient and out-patient health care utilization. In section 5.3 of the chapter, econometric analysis has been done for in-patient treatment to identify the economic and non-economic factors which influences people's choice regarding utilization of health care. In section 5.4, econometric analysis for out-patient treatment has been to identify the economic and non-economic factors which influence people's choice regarding utilization of health care. Finally, section 5.5 is the conclusion of the chapter.

5.2 Model of Health Care Utilization for both In-patient and Out-patient Treatment

5.2.1 Conceptual Framework

In this chapter, we have tried to indentify the factors which are responsible regarding people's choice of health care institution for utilization of health care regarding both in-patient and out-patient treatment. In most of the studies related to choice for health care, since the pioneering work of Grossman (1972), empirical specification for such a model starts from a behavioral model of utility maximization, where utility depends on health and the consumption of other goods, besides medical care. On experiencing an illness, an individual is hypothesized to choose among various treatment alternatives so as to maximize total utility subject to his/her budget constraint. If there are k alternatives, the individual i will choose that particular one which maximizes his/her utility (U_{ik}).

Direct utility function of the consumer (U_{ik}) is represented by

$$U_{ik} = U_{ik}(H_{ik,}C_{ik}) \qquad\qquad (1)$$

Where, H_{ik} is the expected health status after receiving treatment from provider k and C_{ik} is the consumption of non-health care goods which may depend upon the choice k because of the pecuniary and non-pecuniary costs of treatment from provider k.

Since, it is difficult to get estimates of H_{ik} and C_{ik} for a developing country, the usual assumption is to relate H_{ik} and C_{ik} to some observable variables like $X_{i,}Z_{ik,}H_{0,}I_{i}, P_{ik,} and T_{ik}$.

Then, the functional forms of H_{ik} and C_{ik} are

$$H_{ik} = H_{ik}(X_i, Z_{ik}, H_0) \text{ .... } (2)$$

$$C_{ik} = I_i - P_{ik} - wT_{ik} \quad \text{ .... } (3)$$

The function $H_{ik}(X_i, Z_{ik}, H_0)$ in equation (2) is a health care production function with X_i a vector of observable attributes of individual *i,* including those of neighborhood where they live; Z_{ik} is a vector of attributes specific to facility *k* and H_0 is consumer's initial health status. In the budget constraint equation (3), I_i is the relevant income variable, P_{ik} is the price of choosing provider *k, w* is the opportunity cost of time T_{ik}, which in the complete model of Ellis and Mwabu (2004) included time spent travelling to and from facility k and time spent in receiving treatment. In Ellis and Mwabu (2004), C_{ik} has been expressed in functional form where I_i, P_{ik} and T_{ik} entered explicitly instead of linear equation form like equation (3) in order to avoid internal inconsistency often arising due to lack of uniform unit of measurement as follows

$$C_{ik} = C_{ik}(I_i, P_{ik}, T_{ik}) \text{ .... } (4)$$

5.2.2. Modeling of Utilization Health Care for Rural Goalpara and Limitations:

Substituting equation (2) and (4) in equation (1), the indirect utility function for rural Goalpara can be considered as

$$U_{ik} = U_{ik}(X_i, Z_{ik}, H_0, I_i, P_{ik}, T_{ik}) \text{ .... } (5)$$

A decision maker (k) faces a choice among *i* alternatives. U_{ik} is the true but unobservable (latent) utility for alternative *i*. X_i is a vector of demographic variables related to the patient: gender (*GEN*), Caste (*CASTE*), age *(AGE)*, years of education *(EDU)*, severity of ailment *(SEVERE)* and the localities of residence *(BLOCK)*. All the health care institutions in the study area have claimed to be well equipped with required health care infrastructure and manpower. Hence, Z_{ik} is a vector of facility characteristics takes into account two facts: whether the chosen health care facility is nearest one (within 1km) or not from the residence of the patient (NEAREST) and whether the condition of the road via which the patient had to go for utilizing health care is all-weather motorable or not (ROAD). In this study, initial heath status H_0 has been assumed to be good for every patient who has undergone either in-patient or out-patient treatment. So, H_0 has been dropped in this study. Crucial economic variables such as income of the household in terms of monthly per capita expenditure *(MPCE)*, expenditure incurred in the health care utilization *(HEXP)* process excluding travel cost are taken into consideration. Our study considers patients from all age groups i.e., the patients from both dependent and independent age group. So, it is not possible to have uniform measure of opportunity cost of health care all patients in monetary wage. Besides, it has been observed that during the study period even considerable percentage of individuals belonging to the independent age group were involuntarily unemployed. In Indian context, Gupta and Dasgupta (2002) considered number of work days affected by illness for measuring opportunity cost of health care. But, this idea is quite subjective and depends upon the economic condition of the household to which the patient belongs in the study area. So, this factor has been dropped. Besides, travel time and cost differs depending upon the mode of travel. So, to have a uniform set of measurement, distance from the patient's residence to the particular kind of health care *(DISNCE)* enjoyed by the patient in kilometers will be a better measuring scale. So, distance to be travelled for obtaining particular kind of health care *(DISNCE) as* another variable representing economic condition of the household to which the patient belongs to. It should be worth to mention here that this variable has been used as a proxy of capacity to pay keeping other cost constant in the fourth chapter.

5.2.3. Modeling of Utilization In-patient Health Care for Rural Goalpara

In–patient health care is often unpleasant; still people demand it for the sake of betterment of their health. In Assam, there are provision of rural public health care network, urban public health care provision, urban centered private health care provision and a few number of trustee hospitals also. In general, it is believed that except the urban centered private health care provision, remaining health care institutions are quite inexpensive. In reality, there are hidden charges like user charge, transportation, medicines, tests, diets and even bribes which have made the public sector health care quite expensive specially in case of in-patient health care in India (Gupta and Dasgupta, 2002). The decision to choose between different health care providers is influenced by severity of ailment and various economic and non-economic factors.

So, an attempt has been done through logistic regression model to examine various economic and non-economic factors influence people's choice between Urban Secondary Health Care institutions (USHC) or Rural Primary health Care (RPHC) institutions even for those ailments where Rural Basic health care institutions are sufficient provide in-patient health care.

In this static discrete choice model, an individual *i* has two alternatives: *USHC=0* and *RPHC =1* so as to maximize utility. A person will choose *k=m* where m=0, 1 if and only if it maximizes his utility. In other words, if Y_i is a random variable whose value (*k*=0 or 1) indicates the choice made by person *i,* the probability of choosing alternative 1 over 0 is

$$\Pr(Y_i = 1) = \Pr(U_{i1} > U_{i0}) \quad \text{...} \quad (6)$$

Now, logistic regression model can be used to calculate the probabilities of choosing the binary alternatives as follows

$$\Pr(Y_i = 1) = \frac{1}{1+e^{-\beta_i X_k}} \quad \text{...} (7)$$

Where, $\Pr(Y_i = 1)$ is the probability of utilizing *RPHC*; *β* is a vector of unknown coefficients; and *X* is the vector of covariates explained in section 5.2.2.

If the probability of utilizing *RPHC* is $\Pr(Y_i = 1)$ and the probability of utilizing *USHC* is $\Pr(Y_i = 0)$, the *log odds ratio* of using *RPHC to USHC* is

$$\log\{\frac{\Pr(Y_i = 1)}{P_r(Y_i = 0)}\} = \beta_0 + \beta_1 \ln MPCE + \beta_2 \ln HEXP + \beta_3 DISNCE + \beta_4 BLOCK + \beta_5 ROAD + \beta_6 EDU + \beta_7 AGE$$
$$+ \beta_8 CASTE + \beta_9 GEN + \beta_{10} SEVERE + \beta_{11} NEAREST \text{..} (8)$$

Here, log transformations of MPCE and HEXP have been done as standard deviation of these two variables is very high.

5.2.4. Application of Static Discrete Choice Model in the Analysis of Out-patient Health Care Utilization for Rural Goalpara

In India, government spends an insignificant amount on health care services. Automatically, out-of-pocket expenditure for health care becomes high even in case of out-patient care in the formal health care not only in case of private sector but also in case of public sector. Hidden charges like user charge, transportation, medicines, tests, diets and even bribes which have made the public sector health care quite expensive in case of out-patient health care also. So, formal health care cannot be used by all. In contrast to that, informal kind of health care is less costly, easily accessible particularly in rural areas and sometimes effective also.

In this study, regarding out-patient health care utilization, initially ordered logit model was applied as there were three alternative modes of out-patient health care choice *IHC, RPHC* and *other than IHC and RPHC* which are of vertical order regarding quality of services. Here, dependent variable associated with higher value means better one. So, by assuming *IHC=0, RPHC=1* and *other than IHC and RPHC=3,* ordered logit model was introduced. But, unfortunately, this model fails to satisfy the *parallel slope assumption* for the data set in this study. As per Borooah (2001), "if one does have reason for believing that the parallel slope assumption is not valid then the model ought to be estimated using the method of multinomial logit model, notwithstanding the fact that the dependent variable is clearly ordinal." So, multinomial logit model has been used later on.

So, individual i have three alternatives: *IHC=0, RPHC=1* and *Other than IHC and RPHC=2* so as to maximize utility. A person will choose $k=m$ (where, $m=0, 1, 2$) if and only if it maximizes his utility. In other words, if Y_i is a random variable whose value ($k=0, 1, 2$) indicates the choice made by person i, the probability of choosing alternative 2 over 0, 1 is

$$\Pr(Y_i = 2) = \Pr(U_{i2} > U_{i0}, U_{i1}) \text{ .... (9)}$$

Now, multinomial logit model can be used to calculate the probabilities of choosing the alternative j.

5.2.4. a. Multinomial Logit Model

This approach used mostly is based on random utility theory (McFadden, 1974). According this theory, given a choice between M alternatives ($j=1,2,3,....,M$), the utility that the i th person ($i=1,2,3, ...N$) derives from the j th alternative may be represented as U_{ij} choosing the one which maximizes her utility. This individual function can be divided into a systematic component V_{ij} which considers the effect of the explanatory variables (measurable or observable by the modeler attributes) and a random component E_{ij} that takes into account all the effects not included in the systematic component of the utility function; for example, the capacity of the modeler to observe all the variables that have an influence in the measurement errors, differences between individuals incorrect attributes and the randomness inherent in human nature (Borooah,2001).

In this regard, one commonly used model is Multinomial Logit Model, which is derived assuming that the random error terms E_{ij} are independently identically distributed with Weibull distribution $F(E_{ij}) = \exp[\exp(-E_{ij})]$, then probabilities of different outcomes, are defined as follows

$$P_i(Y_i = j) = \frac{e^{\beta_j X_i}}{\sum_{j=1}^{M} e^{\beta_j X_i}} \text{ .... } (10)$$

Where, $P_i(Y_i = j)$ is the probability of using 'j' kind of health care facility, X_i is a vector of explanatory variables and β_j are the coefficients which are to be estimated by using maximum likelihood estimation. As the $\sum_{j=1}^{M} P_i(Y_i = j) = 1$, only *M-1* of the probabilities can be determined simultaneously. Consequently, the multinomial logistic model is indeterminate as it is a system of M equations in which only M-1 independent unknowns. So, each *M-1* probabilities have to be expressed in terms of the reference category.

Assuming the first category as the reference category,

$$P_i(Y_i = 1) = \frac{1}{1 + \sum_{j=2}^{M} e^{\beta_j X_i}} \text{ .... } (11)$$

If the last category is a reference category,

$$P_i(Y_i = M) = \frac{1}{1+\sum_{j=1}^{M-1} e^{\beta_j X_i}} \quad \text{.................................} (12)$$

5.2.5. b. Application of Multinomial Logit Model in the Analysis of Out-patient Health Care Utilization for Rural Goalpara

Applying multinomial logit model in the modeling of utilization of out-patient health care for rural Goalpara,

$$\Pr(Y_i = j) = \frac{e^{\beta_j X_i}}{\sum_{j=0}^{2} e^{\beta_j X_i}} \quad \text{...} (13)$$

Where, $\Pr(Y_i = j)$ is the probability of utilizing j kind of health care service; β_j is a vector of unknown coefficients; and X_i is the vector of covariates explained in section 5.2.2.

If the last category *Other than IHC and RPHC* is a reference category,

$$\Pr(Y_i = 2) = \frac{1}{1+\sum_{j=0}^{1} e^{\beta_j X_i}} \quad \text{...............................} (14)$$

So, log risk ratio of using *IHC* for out-patient care is

$$\log\{\frac{\Pr(Y_i = 0)}{P_r(Y_i = 2)}\} = \beta_0 + \beta_1 \ln MPCE + \beta_2 \ln HEXP + \beta_3 DISNCE + \beta_4 BLOCK + \beta_5 ROAD + \beta_6 EDU + \beta_7 AGE$$
$$+ \beta_8 CASTE + \beta_9 GEN + \beta_{10} SEVERE + \beta_{11} NEAREST \text{.....................................} (15)$$

Log risk ratio of using *RPHC* for out-patient care is

$$\log\{\frac{\Pr(Y_i=1)}{P_r(Y_i=2)}\} = \beta_0 + \beta_1 \ln MPCE + \beta_2 \ln HEXP + \beta_3 DISNCE + \beta_4 BLOCK + \beta_5 ROAD + \beta_6 EDU + \beta_7 AGE$$
$$+\beta_8 CASTE + \beta_9 GEN + \beta_{10} SEVERE + \beta_{11} NEAREST \ldots\ldots\ldots\ldots (16)$$

Here also, log transformations of MPCE and HEXP have been done as standard deviation of these two variables are very high.

5.3 Variables

Drawing from the model, a number of economic and non-economic factors have been identified as influencing people's choice regarding utilization health care service for in-patient and out-patient treatment which are the dependent variable in the *log-odds ratio* and *log- risk ratio* equations. All the variables and their respective measures are described here.

i) MPCE: Monthly Per Capita Expenditure (MPCE) of the household to which the patient belongs is assumed as the proxy of income in this study. This is one of the economic variables which reflect the capacity to pay. It is a quantitative variable. As all ready mentioned, in the sample data set, as the standard deviation of the variable MPCE is very high, log transformation of MPCE (lnMPCE) has been done. The co-efficient of lnMPCE will show the amount and the direction by which log-odds ratio for in-patient and log-risk ratios for out-patient treatment change as result of change in lnMPCE by one unit. In other words, the co-efficient of lnMPCE captures the effect of economic condition of the household to which the patient belongs on the log-odds ratios of in-patient and log-risk ratio of out-patient treatment.

ii) HEXP: Another important economic variable derived from the model is Health Care Expenditure (HEXP) that has been incurred in the respective ailment episode. This is also a quantitative variable. Like MPCE, HEXP variable has also high standard deviation as a result of which log transformation of the variable has been done which is represented lnHEXP. Thus, the coefficient of lnHEXP will give the impact of change in lnHEXP by one unit on the amount and the direction of log-odds ratio for in-patient and log-risk ratio for out-patient treatment.

iii) DISNCE: Distance from the patient's residence to the utilized health care institution (DISNCE) is a quantitative factor. It, actually, reflects the cost of travel and time a patient is capable to bear in order to have particular type of treatment. It is also a quantitative variable. Co-efficient of DISNCE captures the effect of economic condition of the household to which the patient belongs on the log-odds ratios of in-patient and log-risk ratio for out-patient treatment. The co-efficient of DISNCE will show the amount and the direction by which log-odds ratios for in-patient and log-risk ratio for out-patient treatment changes as result of change in DISNCE by one unit.

iv) BLOCK: Balijana is the nearest block to Goalpara town as this block is just 8 km away from Goalpara town where one district civil hospital and five private nursing homes and two trustee hospitals are existed. So, the people of this block have the easy access to not only Rural Public Health Care (RPHC) but also to Urban Secondary Health care (USHC) and Private Health Care. Unlike Balijana block, Rangjuli block is 60 kilometer away from both Goalpara town and Kamrup metro; hence access to USHC and Private Health Care Institution is not so easy. One good thing about this block is that there exists one FRU. In case of Kharmouza block also, it is 30 kilometer away from Goalpara block, where RPHC is relatively easily available than other types of formal health care. One recently proposed FRU is in nearby Lakhipur town. But, in these two blocks, any kind of secondary health care is virtually non-existent. This difference in the access to health care between Balijana block and other two blocks can be captured by a dummy variable BLOCK.

- BLOCK =1, if the block is Balijana, BLOCK = 0 otherwise.

Thus, the coefficient of BLOCK captures the differential effect on the log-odd ratio for in-patient and log-risk ratio for out- patient treatment for patients from Balijana block over the other two blocks.

v) EDU: Education (EDU) is also a quantitative variable which provides the information regarding years of education attained by the patient. Thus, the co-efficient of EDU will represent the amount and the direction of change in the log-odds ratios and log-risk ratios for in-patient and out-patient treatment respectively as a result of change in the explanatory variable EDU by one unit.

vi) AGE: In this study, all the patients are categorized into two groups depending upon their age: Dependent age group (between 0-15 years age and 60 years and above) and Independent age group (15-60years) as already explained in chapter iv. So, this demographic variable has been expressed as a qualitative variable having two categories, one dummy variable is introduced for that.

- AGE=1 if the patient is from independent age category; AGE=0 otherwise.

So, the coefficient of AGE captures the differential effect on the log-odds ratio and log-risk ratio of respective type of treatment for patients from independent age group over patients from dependent age group.

vii) ROAD: Road condition is a qualitative variable having two categories as all weather motorable road and season specific motorable road. Hence, one dummy variable will be introduced.

- ROAD=1, if the road is all weather motorable; ROAD=0 otherwise.

Thus, the coefficient of ROAD captures the differential effect on the log-odds ratio of in-patient and log risk ratio for out-patient treatment for patients from areas having all weather motorable roads over patients from areas not having all weather motorable roads.

viii) NEAREST: The variable **NEAREST** has been used to capture the location of the health care facility. To show whether the particular health facility is the nearest one from the patient's residence or not, one dummy variable will be introduced.

- NEAREST=1, if health facility chosen is nearest one (within 1km); NEAREST =0 otherwise.

ix) SEVERITY: Condition of ailment is a qualitative demographic variable in this study categorized as 'Severe' and 'not-Severe'. So, there will be one dummy variable.

- SEVERITY=1, if the ailment is severe; SEVERITY= 0 otherwise.

Co-efficient of SEVERITY measures the differential impact of condition of ailment as severe over those whose conditions are not serious on the log-odds ratios and log-risk ratios of treatment.

x) CASTE: In this study, caste is another demographic qualitative variable having two categories: ST/ SC, Other than ST/SC category.

- CASTE=1, if the patient is from other than SC/ST category; CASTE=0 for SC/ST category.

Coefficient of another explanatory variable CASTE will show the differential impact on the log-odds ratio and log risk ratio of treatment for other than SC/ST category over SC/ST category.

xi) GEN: Gender, being a qualitative demographic variable having two categories: male and female, one dummy variable is introduced for it.

- GEN=1, if the patient is male one; otherwise 0.

Thus, the coefficient of GEN captures the differential effect male patients over female patients on the log-odds ratios and log-risk ratios for in-patient and out-patient treatment respectively.

5.4. Results of Econometric Analysis for In-patient Treatment

For estimating the log-odds ratio equation for in-patient treatment represented by equation (9), logistic regression function has been run with the help of SPSS 18.0 package. Initially, all the eleven explanatory variables are included in the model. But, in that case the log-likelihood values approaches to zero and maximum likelihood estimates do not exist. There may be complete separation in the data. As the variables *CASTE, NEAREST* and *BLOCK* have been dropped one by one, the problem disappeared. Finally, eight variables are included in the model, namely, $GEN, AGE, EDU, SEVERE, ROAD, DISNCE, \ln MPCE, \ln HEXP$ .Now,log likelihood values improved and the relationship between the response variable and combination of explanatory variables has been accepted on the basis of statistical significance of the chi-square value of the final model. The value of chi-square test of 106.021 with a p-value < 0.0001 tells us that the model as a whole with the above mentioned eight variables fits significantly better than a model having no explanatory variable.

When all the eight explanatory variables are included in the model, good R-Square values have been observed in table 5.1 which represents the explanatory power of the model. Cox and Snell R-Square of the model are little bit smaller than Nagelkarke R-Square because Cox and Snell R-Square ranges from 0 and 0.75 whereas the other lies between 0 and 1.

Table 5.1: Model summery for in-patient treatment

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
59.871	0.549	0.771

Source: Based on primary data

From table 5.2, it has been clear that in-case of in-patient treatment, log odds-ratio between *RPHC* and *USHC* have shown statistically significant relation with all the explanatory variables except *ln MPCE, GEN, AGE.* Still, those, three explanatory variables have not been dropped from the model as their exclusion reduces the value of both Cox and Snell R-square and Nagelkerke R-square value.

The co-efficient of *lnMPCE,* being non-significant, does not have any impact on the log odds-ratio between *RPHC* and *USHC* in case of in-patient treatment. So, household income does not have any impact on choice in-patient health care.

But, another variable representing capacity to pay or the economic condition of the household to which the sample patient belongs is *lnHEXP*. As the value of the coefficient for *lnHEXP* is -4.640, a unit increase *lnHEXP* will reduce the log-odds ratio of *RPHC* versus *USHC* by 4.640 at 1% level of significance. This finding reveals that the expenditure on health care has a negative effect on the log- odds ratio of using *RPHC* to *USHC*. From Exp (B) column, it is clear that a unit increase in ln*HEXP* results in increase in the probability of using *RPHC* by just 0.010 times the increase in the probability of utilizing *USHC* kind of care. That means if somebody has more capacity to incur health expenditure, more likely she will go for *USHC* instead of *RPHC* for in-patient health care even for those ailments where *RPHC* is sufficient for treatment.

The value of the coefficient for *EDU* is -0.236 at 5% level of significance. This finding reflects the fact that a unit increase in *EDU* will lead to decline the log-odds ratio of *RPHC* to *USHC* by 0.236 holding other factors constant at 5% level of significance. So, this finding indicates the negative impact of level of education on the log-odds ratio of *RPHC* to *USHC*. In this case, value of Exp (B) is 0.790 meaning a unit increase in *EDU* results in the increase in the probability of utilizing the *RPHC* kind of care for in-patient treatment 0.790 times the increase in the probability of the utilizing *USHC* kind of care. So, patients with higher level of education are more likely to use *USHC* kind of care for in-patient treatment than the *RPHC* kind of care even for that ailment which can be treated in nearest *RPHC*.

DISNCE is the variable representing capacity to pay or the economic condition of the household to which the sample patient belongs to. The value of the coefficient for *DISNCE* is -0.156 at 1% level of significance which implies one unit increase in the variable *DISNCE* will lead to decrease in log-odds ratio between *RPHC* to *USHC* for in-patient treatment by 0.156. So, the co-efficient of *DISNCE* captures the negative effect of economic condition of the household to which the patient belongs on the log-odds ratios of *RPHC* to *USHC* for in-patient treatment. Again, the value of Exp (B) is 0.855. So, one unit increase in the explanatory variable *DISNCE* will increase in the probability of choosing *RPHC* for in-patient treatment 0.855 times the increase in the probability of utilizing *USHC*. So, if somebody capable to bear travel cost and time more likely choose *USHC* for in-patient than *RPHC* institution for even for those ailments where *RPHC* is sufficient for treatment.

The value of the coefficient for *SEVERE* is -3.252 at 5% level of significance which implies if the ailment is serious, it will lead to a decline in log-odds ratio between *RPHC* to *USHC* for in-patient treatment by 3.252. In this case, value of Exp (B) is 0.039. So, when the ailment is serious, there is possibility of using *RPHC* just 0.039 times the possibility of using *USHC* for in-patient treatment. In other words, when the ailment is not serious more likely patients prefer *RPHC* for in-patient treatment. Oppositely, if the ailment is serious, there is more possibility of utilizing *USHC* institution for in-patient care.

The co-efficient of GEN being non-significant does not have any impact on the log-odds ratio between *RPHC* and *USHC* in case of in-patient treatment. So, a positive social picture has been observed as there is no difference between male and female patients regarding utilization of in-patient health care.

Table 5.2: Results of Logistic Analysis for In-patient Health Care Utilization

Variables	Estimated Coefficients/values	Exp(B)
lnMPCE	0.142 (0.037)	0.868
lnHEXP	4.460*** (14.934)	0.010
EDU	- 0.236** (3.638)	0.790
DISNCE	-0.156*** (9.241)	0.855
SEVERE	-3.252** (4.076)	0.039
GEN	-0.484 (0.259)	
AGE	-0.911 (1.108)	0.616
ROAD	2.946*** (8.048)	19.026
Constant	4.433*** (17.040)	84.157

Source: Primary Data collected from field survey

Notes: a) Values in the bracket represents Wald Chi square test; b) *** and ** represent significance at 1% and 5% level;

Coefficient of another variable AGE is not statistically significant reflecting the fact that whether a patient is from dependent age group or independent age group, it has nothing to do with the choice between *RPHC* and *USHC* institution for in-patient treatment. So, this result also reflects some positive signal about the society.

Coefficient of another dummy variable ROAD is -2.946 at 1% level of significance. That means if the road is all weather motorable, the log-odds ratio between *RPHC* and *USHC* will decline by 2.946. Value of Exp (B) is 0.053. So, when all weather is motorable, there is possibility of using *RPHC* is 0.053 times the possibility of using *USHC* for in-patient treatment. In other words, if the road is all weather not motorable, more likely patients prefer *RPHC* for in-patient treatment. On the other hand, if the road is all-weather motorable, there is more possibility of utilizing *USHC* institution for in-patient care even for that ailment where *RPHC* is sufficient for treatment.

The intercept term, which captures the mean effect of the variables not included in the model, is positive and significant at 1% level of significance.

So, the ultimate *log-odds ratio* equation for in-patient treatment between *RPHC and USHC* is

$$\log\{\frac{\Pr(Y_i=1)}{\Pr(Y_i=0)}\} = 4.433 - 4.640\ln HEXP - 0.156DISNCE - 2.946ROAD - 0.236EDU - 3.252SEVERE \qquad (17)$$

5.5. Results of Econometric Analysis for Out-patient Treatment:

For estimating the log-odds ratio equation for out-patient treatment represented by equation (15) and (16), multinomial logit function has been run with the help of SPSS

18.0 package. Initially, all the eleven explanatory variables are included in the model. But, there is possibly a quasi-complete separation in the data. Either the maximum likelihood estimates do not exist or some parameter estimates are infinite. Validity of the model fit became uncertain. Once the variable BLOCK has been dropped, the problem has been overcome. But from the likelihood ratio test table with the remaining ten explanatory variables, it has been observed that variables *GEN, AGE, EDU* and *ROAD* do not show any kind of statistically significant relation with the dependent variable. Finally, six variables: $CASTE, SEVERE, NEAR, DISNCE, \ln MPCE, \ln HEXP$ are included in the model and the relationship between the response variable and combination of explanatory variables has been accepted on the basis of statistical significance of the chi-square value of the final model as observed from table 5.3.

Table 5.3:Model Fitting Information for Out-patient Treatment

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	524.252			
Final	115.399	408.853	12	.000

Source: Primary Data collected from field survey

The value of chi-square test of 408.853 with a p-value < 0.0001 tells us that the model as a whole with the above mentioned six variables fits significantly better than a model having no explanatory variable. When all the six explanatory variables are included in the model, although Cox and Snell R-Square and McFadden R-Square value of the model are little bit smaller than Nagelkarke R- Square, good Pseudo R-Square values for all have been observed in table 5.4 which represents good explanatory power of the model.

Table 5.4: Pseudo R-Square for Out-patient treatment Model

Cox and Snell	.812
Nagelkerke	.920
McFadden	.780

Source: Primary Data collected from field survey

Now, as there are three categories of the dependent variable and the *Other than IHC and RPHC* is the reference category, there will be two log risk ratio equations: a) log risk-ratio between *IHC* and *Other than IHC and RPHC* and b) log risk ratio between *RPHC* and *Other than IHC and RPHC.*

a) Log risk-ratio between *IHC* and *Other than IHC and RPHC*

From table 5.5, it has been clear that in case of out-patient treatment, log risk-ratio between *IHC* and *Other than IHC and RPHC* have shown statistically significant relation in case of all the six explanatory variables included in the model.

The value of coefficient of lnMPCE is -5.215 with 1% level significance. So, a unit increase lnMPCE will reduce the log-risk ratio of *IHC* versus *Other than IHC and RPHC* by 5.215. Again, from the Exp(B) column, it has been observed that the value of the Exp(B) is 0.013. So, a unit increase in lnMPCE will lead to increase in the probability of using *IHC* by only 0.013 times the increase in the probability of utilizing *Other than IHC and RPHC* kind of care for out-patient treatment. So, capacity to pay has impact on choice of out-patient health care. When the capacity to pay is more, there is lesser possibility of using *IHC* for out-patient health care than *Other than IHC and RPHC.*

Another variable representing capacity to pay or the economic condition of the household to which the sample patient belongs is lnHEXP. As the value of the coefficient for lnHEXP is -2.678, at 1% level of significance. So, a unit increase lnHEXP will reduce the log risk ratio of *IHC* and *Other than IHC and RPHC* for out-patient health care by 2.678. This finding, again, reveals the negative effect of capacity to pay on the log risk ratio of using between *IHC* and *Other than IHC and RPHC.* From Exp (B) column, it is clear that a unit increase in HEXP results in increase in the probability of using *IHC* by just 0.069 times the increase in the probability of utilizing *Other than IHC and RPHC* for out-patient health care. That means if somebody has more capacity to pay, less likely she will go for *IHC* instead of *Other than IHC and RPHC* for out -patient health care.

In case of out–patient health care, another variable quantitative variable *DISNCE* is the variable representing capacity to pay or the economic condition of the household to which the sample patient belongs to. The value of the coefficient for *DISNCE* is -0.210 at 1% level of significance which implies one unit increase in the variable *DISNCE* will lead to decrease in log risk ratio between *IHC* and *Other than IHC and RPHC* for out-patient treatment by 0.210. So, the co-efficient of *DISNCE* captures the negative effect of economic condition of the household to which the patient belongs on the log-risk ratio of *IHC* and *Other than IHC and RPHC* for out-patient treatment also. Again, the value of Exp (B) is 0.811. So, one unit increase in the explanatory variable DISNCE will increase in the probability of choosing *IHC* for in-patient treatment 0.811 times the increase in the probability of utilizing *Other than IHC and RPHC* for out-patient treatment. So, if somebody is capable to bear travel cost and time more likely choose *Other than IHC and RPHC* for out-patient treatment than *IHC* institution.

The value of the coefficient for SEVERE is -2.193 at 1% level of significance which implies if the ailment is serious, it will lead to a decline in log-risk ratio between *IHC* and *Other than IHC and RPHC* for out-patient treatment by 2.193. In this case, value of Exp (B) is 0.054. So, when the ailment is serious, there is possibility of using *IHC* just 0.054 times the possibility of using *Other than IHC and RPHC* for out-patient treatment. In other words, when the ailment is not serious more likely patients prefer *IHC* for out-patient treatment. On the other hand, if the ailment is serious, there is more possibility of utilizing *Other than IHC and RPHC* institution for out-patient care than *IHC*.

Table 5.5: Results of Multinomial Logit Analysis for Out-patient Health Care Utilization

Variables	Estimated Coefficients/values (B)	Exp(B)
IHC		
lnMPCE	-5.215*** (11.316)	.013
lnHEXP	-2.678*** (23.438)	.069
DISTANCE	-0.210*** (6.738)	.811
SEVERITY	-2.913*** (8.622)	.054
NEAREST	2.913* (2.933)	18.421
CASTE	-1.711*** (6.539)	.181
Intercept	5.765*** (19.495)	
RPHC		
lnMPCE	-3.864*** (9.217)	.021
lnHEXP	-1.426*** (9.250)	.240
DISTANCE	-0.390*** (14.116)	.677
NEAREST	4.433 (24.728)	84.147
CASTE	-1.492** (6.394)	.225
SEVERITY	-.868 (1.117)	0.420
Intercept	4.474*** (12.211)	

Source: Primary Data collected from field survey

Notes: a) Values in the bracket represents Wald Chi square test; b) ***, ** and * represent significance at 1%, 5% and 10% level;

The co-efficient of another qualitative variable NEAREST is 2.913 being significant at 10% level. So, the log risk-ratio between *IHC* and *Other than IHC and RPHC* in case of out-patient treatment will increase by 2.913 when the *IHC* is the nearest one. Here, Exp (B) is 18.421. So, when the *IHC* is nearest one, there is possibility of using it 18.421 times larger than the using *Other than IHC and RPHC.* So, when the *IHC* is available within 1km from the residence of the patient, there is possibility of using *IHC* to large extent.

Another variable CASTE is significant at 1% level significance with the value of the co-efficient -1.711. So, if somebody is from other than SC/ST group, the log risk ratio between *IHC* and *Other than IHC and RPHC* in case of out-patient treatment will decline by 1.711. Again, the value of Exp (B) is 0.181. So, when the patient belongs to other than SC/ST group, there is probability of using the *IHC* just by 0.181 times the probability of using other than *Other than IHC and RPHC* in case of out-patient treatment. So, among the non SC/ST group, preference is less for *IHC* in comparison to *Other than IHC and RPHC* for out-patient treatment.

The intercept term, which captures the mean effect of the variables not included in the model, is positive and significant at 1% level of significance.

So, *log-risk ratio* of using *IHC* for out-patient care is

$$\log\{\frac{\Pr(Y_i=0)}{P_r(Y_i=2)}\} = 5.765 - 5.215\ln MPCE - 2.678\ln HEXP - 0.210 DISNCE - 2.913 SEVERE + 2.913 NEAREST - 1.711 CASTE \ldots\ldots (18)$$

b) Log risk-ratio between *RPHC* and *Other than IHC and RPHC*

In case of the log risk-ratio between *RPHC* and *Other than IHC and RPHC* also, statistically significant relation has been observed in case of all the six explanatory variables except NEAREST and SEVERITY.

Regarding utilization of *RPHC* as a source of out-patient treatment, the value of coefficient of lnMPCE is -3.864 with 1% level significance. So, a unit increase lnMPCE will reduce the log risk ratio of *RPHC* versus *Other than IHC and RPHC* by 3.864. Again, from the Exp(B) column, it has been observed that the value of the Exp(B) is 0.021. So, a unit increase in lnMPCE will lead to increase in the probability of using *RPHC* by only 0.021 times the increase in the probability of utilizing *Other than IHC and RPHC* kind of care for out-patient treatment (i.e., Urban Secondary Health Care or any other private health care service). So, capacity to pay has impact on choice out-patient health care. When the capacity to pay is more, there is lesser possibility of using *RPHC* for out-patient health care than *Other than IHC and RPHC* for even some such ailment where *RPHC* is sufficient for treating.

Another variable lnHEXP representing capacity to pay or the economic condition of the household to which the sample patient belongs has shown to be significant 1% level. As the value of the coefficient for lnHEXP is -1.426, a unit increase lnHEXP will reduce the log risk ratio of between *RPHC* and *Other than IHC and RPHC* by 1.426. This finding reveals that the expenditure on health care has a negative effect on the log risk ratio of using *RPHC* to *Other than IHC and RPHC*. From Exp (B) column, it is clear that a unit increase in lnHEXP results in increase in the probability of using *RPHC* by 0.240 times the increase in the probability of utilizing *Other than IHC and RPHC* kind of care (i.e., Urban Secondary Health Care or any other private health care service). That means if somebody has more capacity to pay, more likely she will go for *Other than IHC and RPHC* instead of *RPHC* for out-patient health care for even some such ailment where *RPHC* is sufficient for treating such ailment.

DISNCE is the one more variable reflecting capacity to pay or the economic condition of the household to which the sample patient belongs to. The value of the coefficient for DISNCE is -0.390 at 1% level of significance which implies one unit increase in the variable DISNCE will lead to decrease in log-risk ratio between *RPHC* and *Other than IHC and RPHC* by 0.390 in case of out-patient treatment. So, the co-efficient of DISNCE captures the negative effect of economic condition of the household to which the patient belongs on the log-risk ratios of *RPHC* and *Other than IHC and RPHC* for out-patient treatment in the study area. Again, the value of Exp (B) is 0.677. So, one unit increase in the explanatory variable DISNCE will increase in the probability of choosing RPHC for out-patient treatment 0.677 times the increase in the probability of utilizing *Other than IHC and RPHC* (i.e., Urban Secondary Health Care or any other private health care service). So, if somebody capable to bear travel cost and time more likely choose *Other than IHC and RPHC* for out-patient treatment than *RPHC* institution for even some such ailment where *RPHC* is sufficient for treating such ailment.

Coefficient for SEVERE being non significant does not have any impact on the log risk-ratio between *RPHC* and *Other than IHC and RPHC* for out-patient treatment. So, patients are indifferent regarding choice between *RPHC* and *Other than IHC and RPHC* (i.e., Urban Secondary Health Care or any other private health care service). Patients with serious ailment also go to *RPHC* for out-patient treatment. So, this is a positive sign of NRHM programme.

Coefficient of another variable NEAREST is not statistically significant reflecting the fact that whether particular health care institute stands within 1km or not does not have any influence on the log risk-ratio between *RPHC* and *Other than IHC and RPHC* for out-patient treatment. So, it has nothing to do with the choice between RPHC and Other *than IHC and RPHC* institution (i.e., Urban Secondary Health Care or any other private health care service) for out-patient treatment.

Coefficient of another dummy variable CASTE is -1.492 at 5% level of significance. So, if somebody is from other than SC/ST group, the log risk ratio between *RPHC* and *Other than IHC and RPHC* in case of out-patient treatment will decline by 1.492. Again, the value of Exp (B) is 0.225. So, when the patient belongs to 'other than

SC/ST group, there is probability of using the *RPHC* just by 0.225 times the probability of using other than *Other than IHC and RPHC* in case of out-patient treatment. So, among the non SC/ST group, preference is less for *RPHC* in comparison to *Other than IHC and RPHC*(i.e., Urban Secondary Health Care or any other private health care service) for out-patient treatment.

The intercept term, which captures the mean effect of the variables not included in the model, is positive and significant at 1% level of significance.

So, the ultimate *log-risk ratio* equation for in-patient treatment between *RPHC* and *Other than IHC and RPHC* for out-patient treatment will be

$$\log\{\frac{\Pr(Y_i=1)}{P_r(Y_i=2)}\} = 4.474 - 3.864\ln MPCE - 1.426\ln HEXP - 0.390 DISNCE - 1.492 CASTE$$

....(19)

Conclusion

Influence of various economic and non-economic factors have been examined regarding utilization of both in-patient and out-patient health care differently in this chapter. For analyzing the in-patient health care utilization behavior, logistic regression model has been used whereas for analyzing out-patient health care, multinomial logit model has been used. Accordingly, a number of variables were identified for that purpose and incorporated in the model. In case of in-patient health care utilization, the result reveals that there is more possibility of choosing Urban Secondary Health Care institution by the economically well to do people even for those ailment Rural Primary Health Care is sufficient. Besides, some non-economic factors like road condition and severity of ailment, level of educational attainment all those factors influence people's choice between Urban Secondary Health Care institution and Rural Primary Health Care Institution for in-patient health care. If the road is all weather motorable, patients will more probably go to Urban Secondary Health Care institution for in–patient health care. If somebody is more educated or his/her ailment is considered to be serious by the patient or his/her family, more likely she will go to Urban Secondary Health Care institution for in-patient treatment.

Again, in case of out-patient care also, economic factors plays important role in deciding whether to go to Informal Health Care or Rural Primary Health Care or other than these two. Generally, possibility of using Informal Health Care for out-patient care among the economically weaker section is more than Urban Secondary Health Care and the Private practitioners. Again, like in-patient treatment in case of out-patient treatment also economically better off people are less likely to prefer Rural Primary Health Care. Besides, a few non-economic factors like severity of ailment, caste stratification, location of the health care facility etc. also play important role in choosing between different kinds of out-patient health care facility. In case of out-patient care, when the ailment is not serious or if the patient's is from SC/ST category or when the Informal Health Care is available in the nearest distance, there is more possibility of using Informal Health Care than the Urban Secondary Health Care Services and the Private practitioners in rural Goalpara. In case of Rural Primary Health Care, the only one non-economic factor that is the caste stratification plays important role while there is no importance of the other non-economic factors.

****

References:

Borooah, V.K.(2001), *'Logit and Probit: Ordered and Multinomial Models'*, Sage University Paper Series on Quantitative Applications in the Social Sciences, series no.07-108. Thousand Oaks, CA:Sage.

Ellis,R.P and G Mwabu (2004), 'Demand for Out-patient Medical Care in Rural Kenya' http://www.bu.edu/econ/files/2012/11/dp140ellis.pdf (accessed on 05.11.13)

Grossman, M.(1972), 'On the Concept of Health, Capital and the Demand for Health', *Journal of Political weekly*, vol.80 (2), 223-235.

Gupta, I and P. Dasgupta (2002), 'Demand for Curative Health Care in Rural India:Choosing between Private, Public and No Care' http://www.ncaer.org/Downloads/WorkingPapers/wp82.pdf (accessed on 06.11.13).

McFadden, D.(1973), 'Conditional Logit Analysis of Qualitative Choice Behaviour in P.Zarembka (Ed.), *Frontiers in Econometrics,* New York: Academic Press.

****