Structure of Household Income and Expenditure and Its impact on Poverty Alleviation

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Abstract: The aim of current study is to find determinants to alleviate poverty using data of the Household Income and Expenditure Survey-2010 conducted by the Bangladesh Bureau of Statistics. According to the destination, Multinomial logit model with nominal response is appropriate for determining objective variables. It is common practice that the categorical response has more than two levels. Here, dependent variable calorie intake has four levels and independent variable, level of education has two categories, household members have four categories, household income and household expenditure both have four categories. Determining the significance of explanatory variables for alleviating poverty, maximum likelihood ratio test, Wald test were used. The findings suggest that the parameters estimates under three logit, household members and household expenditure are significantly associated with the poverty. Thus, it can be concluded that this model may play a vital role in alleviation of poverty in Bangladesh as well as in the third world countries.

Key Words: Nominal response, Multinomial Logit, Likelihood Ratio Test, Wald Test, Odd Ratio, Deviance.

I. Introduction

The ILO has been concerned with statistics on the living and working conditions of workers and their families since its founding in 1919. In this regard, several previous International Conferences of Labor Statistician (ICLS) have been passed resolution on household income and expenditure surveys. This last and still existing resolution deals with objectives, frequency and scope of household income and expenditure. The surveys of organization are included units of data collection; basic concepts and definition of Consumption income and expenditure; basic methodology; classifications; tabulation and presentation of results.

In this respect, Bangladesh Bureau of Statistics has been established in 1974 after independence analyzing the characteristics of health, demography and socio-economic conditions etc. Bangladesh Bureau of Statistics carried out various types of Census and Surveys. Household Income and Expenditure Survey (HIES)is one of the most important survey of BBS. Specially, the provision was made to collect data on several socio-demographic characteristics to correlate income, consumption and expenditure pattern with different segments of population. After the independence, Household Expenditure Survey was first carried out in 1973-74 and last in 2010 and poverty is measured by consumption of intake calorie.

Household income consists of all receipts in cash, in kind or in services that are received by the household or by individual members of the household at annual or more frequent intervals. But excludes windfall gains and other such irregular and typically one-time receipts and age 18 below. Do not reduce the net worth of the household through a reduction of its cash, the disposal of its other financial or non-financial assets or an increase in its liabilities. Household income may be defined operationally in terms of (i) income from employment (both paid and self- employment) (ii) property income (iii) income from the production of household service for own consumption and (iv) transfers received.

Household expenditure is defined as the sum of Household consumption expenditure and the non-consumption expenditures of the household. The latter are those expenditures incurred by a household that relate to compulsory and Quasi-Compulsory transfers made to government, non-Profit institutions and other households. Household expenditure represents the total outlay that a household has to make satisfy its needs and meet its ‘legal’ commitments.

According to the 2005 Household and Income and Expenditure Survey, 25.1% of households in Bangladesh lived in extreme poverty. By 2010, the figured had fallen to 17.6%.

In difference of 5 (five) years, poverty alleviation is very poor. So we can consider that there is no proper model or plan or sustainable way to make for poverty alleviation in Bangladesh since the data are in Bangladesh. So by using the survey data, I would like to formulate a proper model to reduce poverty as early as possible with the assistance of multinomial logistic regression.

II. Objective

Household income and expenditure statistics serve a variety of purposes with respect to poverty level measurement, socio-economic condition and other forms of description and analysis such as: analysis of the relationship between income distribution, economic activity and returns to labor, capital and land, analysis labor market relationships between income or some components of income and characteristics of workers, jobs, place of work and job search. Formulation and monitoring of wage policies – including the setting of minimum wages, Analysis of the determinants of consumer behavior, analysis of the generation and uses of income – informal sector income, rural income, financing of consumption expenditure, analysis of savings behavior of individuals in different types of households, analysis of indebtedness, ownership of assets, analysis of the effect on households of drastic sudden changes in economic and social policies such as in the transition economies, analysis the relationship between poverty alleviation and the socio-economic parameters of the households involved to see which factors and constraints might explain poverty alleviation, analysis of the poverty with urban and rural breakdown, analysis about standard of living and nutritional status of the population, analysis on health status and educational level of the population, analysis of distribution of resources under different Social Safety Nets Programs (SSNP), analysis of disability, migration, remittances, micro credit and disasters management. After analyzing the data, it is needed to establish a new formula to alleviate poverty.

III. Review of literature

There is large body of literature that relates income, expenditure and poverty for alleviation of poverty but poverty has not been reduced significantly. In this purpose, there are many researchers worked about this. Some examples are given below:

The world Bank estimates that there was a substantial reduction in the incidence of rural poverty between 1991-92 and 1995-96 (world Bank, 1998), whereas careful estimates by others (e.g., sen 1998) suggested that the reduction of poverty was insignificant over the same period of time. Islamic Development Bank Group, Jeddah, Saudi Arabia in 2011 worked on "Islamic Solidarity Fund for Development Country poverty assessment" has recommended that capability and skill development, Agricultural development by their interventions. Md. Shafiul Azamand KatsushiS. Imai, Economics, School of Social Sciences, University of Manchester, UK worked on "Vulnerability and Poverty in Bangladesh" has recommended that Education is found to be a key element in reducing poverty. Poverty and vulnerability are the highest among households headed by illiterate person; whereas households headed by person having more than higher secondary level education are significantly better poised to cope with risk and uncertainty. So investment in human capital along with other means of social protection and promotion could be instrumental for poverty reduction in Bangladesh. Agricultural households again are more vulnerable than non-agricultural households, which underscores the need for more protection of the agricultural community. The government needs to be creative in renewing and revising strategies and approaches to control the rising food prices and sequentially food inflation as well as the budgetary allocation for poverty alleviation should be increased. K. M. Mustafizur Rahman(2011) worked on "Poverty and Inequality in Bangladesh" The government needs to be creative in renewing and revising strategies and approaches to control the rising food prices and sequentially food inflation as well as the budgetary allocation for poverty alleviation should be increased. Therefore, provisions must be formulated for the evaluation of programs and understanding the impacts as well. PK. Md. Motiur Rahaman (2005) worked on "Development policies And poverty Alleviation in Bangladesh" and said that in view of the large extent of poverty particularly in rural areas of Bangladesh, a wide range of development activities have been implemented and a number of strategies have been set up at the national level by the government and non-government organizations for poverty alleviation. The primary objectives of those development efforts are to accelerate economic growth through agricultural development. The agriculture sector plays a vital role in reducing rural poverty and foresting sustainable economic growth. The linkage between agriculture and non-agricultural sectors in the economy are such that a given increase in production in agricultural sectors usually leads to a more than proportionate increase in production in non-agriculture sectors. Labor intensive activities such as dairy and poultry raising, fish culture, vegetable growing etc. are important strategies for poverty alleviation in agriculture sector in rural areas. Physical infrastructure includes construction of roads, canals for irrigation, rural electrification, etc. Infrastructure development, particularly in rural areas, can also make a considerable contribution to growth through job creation and improvement of access to different economic activities and social services, which lead to food security of the rural poor. Social infrastructure includes educational institutions, health care institutions, post office, banks, etc and Dynamics of Poverty in Rural Bangladesh by PK.Md.Motiur Rahman Noriatsu Yukio Ikemoto recommending that sustainable decline of fertility is crucial for reducing household size, dependency ratio and consequently reducing poverty.

IV. Materials and Methods

Bangladesh Household Income and Expenditure Survey 2010, 2005, 2000 and 1995-96 Data are used in the study which is performed through a collaborative effort among Bangladesh Bureau of Statistics (BBS) by supervising of Macro International organization such as UNDP and UNFPA and Bangladesh Government. As well as they provided financial and technical assistance for the survey. BBS is a periodic survey conducted in Bangladesh as a part to find lacking of the country in order to poverty alleviation and to view comparing worldwide Demographic and Health and socio-economic status through the Surveys program.

In this respect, A nationally representative multistage cluster sample survey of HIES is designed to collect data and provide information on basic national indicators of social progresses and poverty level and socio-economic structure. In HIES-2010 survey of BBS, there are 12240 household were selected where 7840 from rural area and 4400 from urban area under 1000 PSUs through the country which is designed to collect data on education, family members, all types of income such as Wages and salaries, Agricultural activities (seasonal crops and non-seasonal crops, Nonagricultural activities, Other regular cash receipts such as pensions, dividends, rents, interest amounts received from various types of savings, current remittances and local and foreign transfers. The income in kind is mostly the estimated values of the household consumed items such as home grown fruits and vegetables, firewood collected etc. Data were collected form 55580 population where 35894 are rural and 19686 are urban. But at the current study on 9290 people from 2040 household under the 100 primary sampling units selected randomly.

Average monthly income and expenditure per household at current price was estimated at tk. 11479 and tk. 11200 at the national level in 2010.This was Tk. 7203 and tk. 6134 in 2005, Tk. 5842 and tk. 4881 in 2000, Tk. 4366 and tk. 4096 in1995-96 respectively. Per capita monthly income was estimated at taka 2553 in 2010. This was Tk. 1485, Tk. 1128 and Tk. 830 in 2005, 2000 and 1995-96 respectively. Per capita monthly income increased by Tk. 1068 (71.92%) in 2010 compared to 2005 and increased by Tk. 1723 (207.59%) over the year 1995-96.

In the same way average monthly expenditure increased, monthly consumption expenditure per household was taka 11003 in 2010 at the national level. Specially, in rural area, the average consumption expenditure was taka 9436 per month, where as in the urban area, it was found to be tk.15276. In 2005, it was Tk. 5964, Tk. 5165 and Tk. 8315 at national level, rural and urban respectively. The monthly average consumption increased by 84.5% over the year 2005 and by 142.5% over 2000. After analyzing, the consumption expenditure was 98.2% of the total expenditure at national level, 98.2% in rural area and 98.4% in urban area in 2010.But using of data BBS did not establish any feature for poverty reduction.

In the study to establish rapidly poverty alleviation strategy using those data are education, household members, per-month income per-household, per-month expenditure per-household, per-head intake calorie of the selected households. Data gathered were especially relating to consumption income, expenditure and intake calorie. Related information such as demographic and economic characteristics, working activities of those population and housing characteristics are also included. Different descriptive statistics, Multinomial logistic regression with nominal responses will be used to make poverty reduction strategy model by the using respected data. Logistic regression may also be used to develop a model about poverty alleviation.

A response corresponding to wants per head intake calorie within, less than 1400 calorie as poorest, 1400 calorie through 1805 calorie as poorer, 1805calorie through 2122 calorie as poor and more than 2122 calorie as rich denoted as level 1 for 'poorest', 2 for `poorer', 3 for `poor', 4 for `rich', respectively and used as a discrete choice outcome variable Y in the current study. Respondent's education(X_1), Household members(X_2), Per-month Household income (X_3) and Per-month Household expenditure (X_4) are considered as potential covariates to develop a multinomial logit model with response variable Y. The explanatory variables, Education (X_1) is leveled as 1 for `Not read' and 2 for `read', Household members $(X_2)$is leveled as 1 for 'more than 8 members`, 2 for '7 members to 8 members`, 3 for '5 members to 6 members` and 4 for ' 1 member to 4 members', Per-month Per-household Income $(X_3)$ is leveled as 1 for `less than tk. 2500', 2 for `tk. 2500 through tk. 5000', 3 for `tk. 5000 through tk. 7500' and 4 for `more than tk. 7500' and Per-month Per-household Expenditure $(X_4)$ is leveled as 1 for ` Less than tk. 2500', 2 for `tk. 2500 through tk. 5000', 3 for `tk. 5000 through tk. 7500' and 4 for `More than tk. 7500'in the study.

V. Multinomial Logit Model

In statistics, multinomial logit regression sometimes called the multinomial logit model is used for prediction of the probability of occurrence of an event by fitting data to a series of logit functions applying logistic distribution. To fit a multinomial logit model having more than two levels of response variable, one must pay attention to the measurement scale (Hosmer and Lemeshow, 2000). Levels associated with the response variable in the current study are nominal scale. Let Y be a multi-categorical response variable having L nominal levels. Generally, one value typically the first, the last, or the value with the highest frequency of the response variable is designated as the baseline or reference category. The probability of membership in other categories is compared to the probability of membership in the reference category. For a response variable with L categories, multinomial logit model describes:

$${}^{L}C_2=\frac{L(L-1)}{2}$$

Possible pairs of log-odds for comparisons but it is not necessary to develop all logistic regression models instead only some choice of (L-1) pairs are necessary and the rests are redundant.

To formulate the generalized multinomial logit model, let there are k explanatory variables and an intercept term denoted by the $X_i' = (X_{0i}, X_{1i}, X_{2i}, \dots\dots\dots, X_{ki}$ vector length $(k+1)$ where $X_{0i} = 1$ in the analysis involving n independent subjects; The general expression for conditional probability of the lth level of response variable be present given the explanatory variables, is expressed by:

$$\eta_{i1} = P(Y = l|X) = \frac{e^{X_i^{'}\gamma_l}}{\sum_{t=1}^{L} e^{X'_i\gamma_t}};\ l = 1,2,\dots\dots..,L\,;i = 1,2,\dots\dots..,n \tag{1}$$

Where, $\gamma'_1 = (\gamma_{l0}, \gamma_{l1}, \gamma_{l2}, \dots\dots\dots\dots \gamma_{lk})$ is vector of unknown parameters? Without loss of generality, L coded variables $Y_{i1}, Y_{i2}, \dots\dots\dots Y_{iL}$ with corresponding probabilities $\eta_{i1}, \eta_{i2}, \eta_{i3}, \dots\dots \eta_{iL}$ such that $\sum_{l=1}^{L} Y_{i1} = 1$ and $\sum_{l=1}^{L} \eta_{i1} = 1$ for the ith subject can be generated from the response variables Y having L nominal levels. In order to construct the logit function, one level should be chosen as the baseline or referent level and all other levels can be compared to it. The choice of referent level though is arbitrary, generally the last level having highest frequency of the response variable is chosen as referent level (Kutneret al., 2005). Multinomial logit model in general not a linear model in the parameters, logit transformation can be used to make it approximately linear by the principle of generalized linear model (McCullagh and Nelder, 1989). Using the last level L as referent level, only (L-1) meaningful comparison can be done with respect to the referent level to describe the relationship between the response variable and the explanatory variables. Thus the logit for the lth such comparison with respect to referent level is given by:

$$\Psi_1 = \log\left[\frac{\eta_{il}}{\eta_{iL}}\right] = \gamma_{l0} + \gamma_{l1}X_{1i} + \gamma_{l2}X_{2i+\cdots+\gamma_{lk}X_{ki}} = X_i^{'}\gamma_1; l = 1,2,\dots.,(L-1) \tag{2}$$

In terms of the logit function and using the condition $\Psi_L = 0$ the general expression for the conditional probability given Eq. 1 can be written as:

$$\eta_{i1} = P(Y = l|X) = \frac{e^{\Psi_1}}{1 + \sum_{t=1}^{L-1} e^{\Psi_t}};\ l = 1,2,\dots\dots..,(L-1) \tag{3}$$

VI. Maximum Likelihood Estimation

After formulation of the multinomial logit model, the next step is to describe the methods for obtaining estimates of the (L-1) vectors of parameters $\gamma_1, \gamma_2, \dots\dots..,(\gamma_{L-1})$ given by:

$$\gamma_1 = \begin{bmatrix}\gamma_{10}\\ \gamma_{11}\\ \gamma_{12}\\ \vdots\\ \gamma_{1k}\end{bmatrix}, \gamma_2 = \begin{bmatrix}\gamma_{20}\\ \gamma_{21}\\ \gamma_{22}\\ \vdots\\ \gamma_{2k}\end{bmatrix}, \gamma_3 = \begin{bmatrix}\gamma_{30}\\ \gamma_{31}\\ \gamma_{32}\\ \vdots\\ \gamma_{3k}\end{bmatrix}, \dots\dots\dots \gamma_{(L-1)} = \begin{bmatrix}\gamma_{(L-1)0}\\ \gamma_{(L-1)1}\\ \gamma_{(L-1)2}\\ \vdots\\ \gamma_{(L-1)k}\end{bmatrix}$$

Multinomial logit model quantifies the effect of an explanatory variable in terms of the log-odds ratio using Maximum Likelihood Estimation (MLE). The more efficient and precise approach from the statistical viewpoint is to obtain estimates of the (L-1) logits simultaneously instead of sequential binomial logits. To do so, the likelihood for the full data set is required. In order to construct the likelihood function, let the lth category for the response variable Y is selected for ith response. More specifically, for the ith case, $Y_{i1} = 0, Y_{i2} = 0, \dots..,Y_{il} = 1, \dots\dots Y_{iL} = 0$. The probability of this response is given by:

$$P(Y_{il} = 1) = \eta_{il} = (\eta_{il})^0 \times (\eta_{i2})^0 \times \dots\dots \times (\eta_{il})^1 \times \dots\dots (\eta_{iL})^0 = \prod_{l=1}^{L} (\eta_{il})^{Y_{il}} \tag{4}$$

For n independent observations and L levels for the response variable Y, the likelihood function can be constructed by:

$$\varphi = \prod_{i=1}^{n} P(Y_{il}) = \prod_{i=1}^{n} \left[\prod_{l=1}^{L} (\eta_{il})^{Y_{il}}\right] \tag{5}$$

Taking natural logarithm and using the fact that:

$$\sum_{l=1}^{L} Y_{il} = 1$$

For each i, the log-likelihood function is given by:

$$Log_e(\varphi) = \sum_{i=1}^{n}\left[\sum_{i=1}^{L-1}(Y_{il}\Psi_1) - Log_e\left\{1 + \sum_{i=1}^{L-1} e^{\Psi_1}\right\}\right] \quad (6)$$

The likelihood equations can be found by taking the first derivatives of $Log_e(\varphi)$ with respect to each of (L-1) × (K+1) unknown parameters. The maximum likelihood estimates $\gamma_1, \gamma_2, \ldots \ldots . \gamma_{(L-1)}$ of are those values of $\hat{\gamma}_1, \hat{\gamma}_2, \ldots \ldots . \hat{\gamma}_{(L-1)}$, that maximize Eq. 6 and can be obtained by setting the likelihood equations equal to zero and solving for the vectors of parameters. These likelihood equations are non-linear in parameters and can be numerically solved by Newton-Raphson method. Hence one must rely on standard statistical software programs and iterative computation that is used to obtain these estimates. On the other hand, in order to test the significance of covariance, the matrix of second partial derivatives is required to get the information matrix and the estimator of the covariance matrix and consequently the standard error of the maximum likelihood estimators. The generalized form of the elements in the matrix of second partial derivatives is given in Eq. 7 and 8, respectively.

$$\frac{\delta^2 Log_e(\phi)}{\delta\gamma_{lv}\delta\gamma_{lv}} = -\sum_{i=1}^{n} X_{vi}X_{vi}\eta_{il}(1-\eta_{il}) \; ; v = v' = 0,1, \ldots \ldots k \quad (7)$$

$$\frac{\delta^2 Log_e(\phi)}{\delta\gamma_{lv}\delta\gamma_{l'v'}} = \sum_{i=1}^{n} X_{vi}X_{vi}\eta_{il'}(1-\eta_{il}) \; ; l = l' = 1,2, \ldots \ldots \ldots \ldots (L-1) \quad (8)$$

The estimated or observed information matrix, denoted by $I(\hat{\gamma})$is the (L-1) (k+1) × (L-1)(k+l) matrix whose elements are the negatives of the values obtained from the Eq. 7 and 8 evaluated at $\hat{\gamma}$.The estimated standard error (SE) of the maximum likelihood estimator is obtained from the positive square root of principal diagonal of inverse of the observed information matrix $S.E(\hat{\gamma}) = \sqrt{I^{-1}(\hat{\gamma})}$. Although computationally different, the multinomial logit model produces results that are nearly identical to the general 2x2 contingency table having observed cell frequencies a, b, c, d (Collett, 1991). It is notable that in the multinomial logit model, the MLE estimation of the standard error of the estimate is quite close to the estimated standard error derived by using Woolf (1955) approach given by:

$$S.E(\hat{\gamma}) = \left(\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}\right)^{\frac{1}{2}}; \; l = 1,2, \ldots \ldots ., (L-1); \; v = 0,1,2, \ldots k \quad (9)$$

Hence the estimator of the variance of the difference between two coefficients$(\hat{\gamma}_{lv} - \hat{\gamma}_{l'v}; \;\; l \neq l')$ is given by:

$$V(\hat{\gamma}_{lv} - \hat{\gamma}_{l'v}) = V(\hat{\gamma}_{lv}) + V(\hat{\gamma}_{l'v}) - 2cov(\hat{\gamma}_{lv}, \hat{\gamma}_{l'v}) \quad (10)$$

The values for the estimates of the variances and co-variances can be obtained from the software program SPSS through a listing of the estimated asymptotic covariance matrix. The form of this matrix is a little different from the covariance matrix in the binary setting. There are two matrices containing the estimates of the variances and co-variances of the estimated coefficients in each logit and a third containing the estimated co-variances of the estimated coefficients from the different logits. Such matrix for the multinomial logit model is not exhibited in the current analysis. In order to interpret the effect of covariates on response variable, a measure of association called odds ratio, a powerful analytic tool should be defined. The odds ratio, denoted OR, defined as the ratio of odds for a specific level to the odds for the referent level. In a multinomial outcome setting, the odds ratio of outcome Y = *l* versus outcome Y = L for a specific covariate X = r versus X = s is defined by:

$$OR_{lv}(r,s) = \frac{P(Y=l|X=r)/P(Y=L|X=r)}{P(Y=l|X=s)/P(Y=L|X=s)}; l = 1,2, \ldots \ldots ., (L-1) \quad (11)$$

In a multinomial logit model, the response variable Y having L distinct nominal levels,(L-1) logits are generated and consequently, (L-1) parameter estimates and corresponding odds ratios are found for each of the covariates. In case of any significant differences among the parameter estimates or the corresponding odds ratios under different logits are found, then the required multinomial logit model will be established with nominal response.

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VII. Results and Discussion

In order to display the findings of current study, suppose there are L = 4 levels in the response variable and the 4th level having the highest frequency is considered as referent level. There is 4th level response variable, so three logit can be established in the model. By using SPSS, multinomial logit output for nominal response is exhibited in Table: 1 which contains the estimated regression coefficients, estimated approximate standard errors, and the Wald test statistics with associated p-values, the estimated odds ratios, 95% confidence intervals for the odds ratios for the three estimated logits or linear predictors. The results of multinomial logit model can be expressed in the form of odds ratios, telling us more than efficient effected explanatory variable is family member X_2 for every level under each logit and Household expenditure variable X_4 is also effected all levels for two logit under the three logit, how much change there is in the probability of being certain level under study, given a unit change in any other given covariate but holding all others covariates in the analysis constant. More simply, the results tell us how much a hypothesized cause has affected this response, taking the role of all other hypothesized causes into account. A preliminary indication of the importance of the explanatory variables in the model under different logits can be assessed through the Wald statistic. The Wald test is obtained by comparing the maximum likelihood estimates of the slope parameters$\hat{\gamma}_{lv}$, to the estimates of their corresponding standard errors S.E($\hat{\gamma}_{lv}$). The estimates of the standard errors of the estimated parameters can be obtained from Eq. 9. The resulting ratios:

$$W_{1v} = \frac{\hat{\gamma}_{lv}}{S.E(\hat{\gamma}_{lv})}$$

Table l: Estimated coefficients, estimated standard errors, Wald chi-square statistics with degrees of freedom and p-values, odds ratios and 95% confidence interval of odds ratios for the multinomial logit model to the HIES-2010 data from BBS.

Parameter Estimates

Intake Kcal. Per-head Logit	Explanatory variable	$\hat{\gamma}_{lv}$	S.E($\hat{\gamma}_{lv}$)	W_{lv}	df	Sig.	OR_l	95% CI for OR_l	
								LB	UB
1(1/4), poorest	Intercept	-4.632	.369	157.149	1	.000			
	[x1=1]	-.134	.226	.351	1	.553	.875	.562	1.362
	[x1=2]	0^b	.	.	0	.	.	.	.
	[x2=1]	2.362	.622	14.403	1	.000	10.608	3.133	35.920
	[x2=2]	2.116	.460	21.126	1	.000	8.295	3.365	20.447
	[x2=3]	1.525	.298	26.261	1	.000	4.596	2.565	8.237
	[x2=4]	0^b	.	.	0	.	.	.	.
	[x3=1]	-.682	.470	2.105	1	.147	.506	.201	1.270
	[x3=2]	-.145	.346	.175	1	.675	.865	.439	1.704
	[x3=3]	.050	.294	.028	1	.866	1.051	.590	1.870
	[x3=4]	0^b	.	.	0	.	.	.	.
	[x4=1]	4.444	.560	62.955	1	.000	85.076	28.386	254.981
	[x4=2]	3.212	.377	72.592	1	.000	24.820	11.856	51.960
	[x4=3]	1.536	.344	19.906	1	.000	4.646	2.366	9.123
	[x4=4]	0^b	.	.	0	.	.	.	.
2(2/4), poorer	Intercept	-2.991	.201	220.546	1	.000			
	[x1=1]	-.093	.139	.447	1	.504	.911	.694	1.197
	[x1=2]	0^b	.	.	0	.	.	.	.
	[x2=1]	1.922	.357	29.059	1	.000	6.836	3.398	13.750

	[x2=2]	2.064	.242	72.501	1	.000	4.881	4.900	12.675
	[x2=3]	1.095	.179	37.294	1	.000	2.989	2.103	4.247
	[x2=4]	0b	.	.	0	.	.	.	.
	[x3=1]	-.108	.296	.133	1	.715	.898	.502	1.604
	[x3=2]	.357	.208	2.946	1	.086	1.429	.951	2.148
	[x3=3]	.244	.177	1.896	1	.168	1.277	.902	1.807
	[x3=4]	0b	.	.	0	.	.	.	.
	[x4=1]	2.185	.450	23.624	1	.000	8.892	3.684	21.461
	[x4=2]	2.007	.234	73.585	1	.000	7.440	4.704	11.769
	[x4=3]	1.221	.190	41.316	1	.000	3.390	2.336	4.918
	[x4=4]	0b	.	.	0	.	.	.	.
3(3/4), poor	Intercept	-1.881	.151	154.935	1	.000			
	[x1=1]	-.139	.123	1.293	1	.256	.870	.684	1.106
	[x1=2]	0b	.	.	0	.	.	.	.
	[x2=1]	.985	.321	9.422	1	.002	2.679	1.428	5.026
	[x2=2]	.898	.223	16.235	1	.000	2.454	1.586	3.797
	[x2=3]	.581	.147	15.598	1	.000	1.789	1.340	2.387
	[x2=4]	0b	.	.	0	.	.	.	.
	[x3=1]	.027	.263	.010	1	.920	1.027	.613	1.720
	[x3=2]	.168	.191	.778	1	.378	1.183	.814	1.721
	[x3=3]	.148	.154	.928	1	.335	1.160	.858	1.568
	[x3=4]	0b	.	.	0	.	.	.	.
	[x4=1]	.213	.578	.135	1	.713	1.237	.399	3.838
	[x4=2]	.718	.219	10.796	1	.001	2.050	1.336	3.146
	[x4=3]	.757	.155	23.771	1	.000	2.133	1.573	2.891
	[x4=4]	0b	.	.	0	.	.	.	.

The reference category is: Rich (level 4)

Under the null hypotheses $H_0: \gamma_{lv} = 0$, will follow a standard normal distribution and hence equivalently:

$$W_{lv} = \frac{\hat{\gamma}^2{}_{lv}}{[S.E(\hat{\gamma}_{lv})]^2}$$

will follow chi-square distribution with single degree of freedom. Examination of the Wald statistics in Table:-1 suggests that two of the explanatory variables may contribute to the model. From the statistical point of view, the findings exhibited in Table 1, all the explanatory variables irrespective of their levels under different logits except level of education are significantly associated with the response variables at 5% level of significance.

For polychotomous explanatory variable, we can expand the number of odds ratios to include comparisons of each level of the variable to a reference level for each possible logit function. Thus the one estimated coefficients for the design variable Education index(X_1), three estimated coefficient Household members index (X_2)which estimate the log odds for level 1= more than 8 members, for level 2= 7 to 8 members, for level 3= 5 to 6 members versus the reference value of level 4 = 1 to 4 members, suggest that there is no categories are similar since neither Wald statistics are significant. The sign and magnitude of the estimated coefficients for the accumulated design variables, Household members and Per-month Household expenditure, suggest that the log odds of every level is differ significantly and are of dissimilar magnitude within each of the three logit functions (test are not presented). The likelihood test ratio after accumulation of each level of Household Income (X_3) under different logit yields the value G=253.332with four degree of freedom .

Hauck and Donner (1977) examined the performance of the Wald test and found that it behaved in an aberrant manner, often failing to reject the null hypothesis when the coefficient was significant. They recommended that the more robust likelihood ratio test should be used to justify the significance of individual predictor. Jennings (1986) has also looked at the adequacy of inferences in logistic regression based on Wald statistics. In order to avoid the uncertainty of inferences, he suggested that both the likelihood ratio test G and the WaldtestW_{lv}require to test the significance of the maximum likelihood estimates for$\hat{\gamma}_{lv}$. The likelihood ratio test G is nothing but the change in the deviance of a model with single covariate and a full model where minus twice the log likelihood is known as deviance and denoted by D (Agresti, 2002). Under the same null hypotheses, likelihood ratio tests G follow chi-square distribution with (L-1) × (M-1) degrees of freedom. Here L and M are the number of levels of response variable and the corresponding explanatory variable, respectively. The output of the likelihood ratio tests are shown in Table: 2 and it can be concluded that all the explanatory variables included in the model are significantly associated with the response variable at 5% level of significance.
In order to fit a model, it is important to have tools to test for lack of fit, especially important for the multinomial logit model, whose fit is notoriously difficult to visualize. Such tools are remarkably scarce in multinomial logistic regression applications (Goeman and le Cessie, 2006). In such a situation, Deviance and Pearson's chi-square goodness-of-fit test can be employed whether the model adequately fits the data. In these tests, lack of fit is indicated by the significance value less than 0.05. To support the effective of the fitted model, a significance value greater than 0.05 is needed. If no warning message is given from the program or the number of subpopulations with zero frequencies is small with p>0.05, it may be concluded that the model fits the data well. The large p-values for both the goodness-of-fit tests signify the adequacy of the fitted multinomial logit model.
The main objective of this study was to test the inequality of the two odds ratios, $H_0: OR_{1v} \neq OR_{2v}$ (v=1,2,3) under three different logits, similarly, $H_0: OR_{2v} \neq OR_{3v}$ which is equivalent to a test that the log-odds for Y = 1,Y=2 and Y=3 is not equal, simply $H_0: OR_{1v} \neq OR_{2v} \neq OR_{3v}$. The simplest way to obtain the point and interval estimate is from difference between the two estimated slope coefficients in the multinomial logit model. Using the output of the asymptotic variance-covariance matrix produced by the multinomial logit model, it can easily be obtained the estimator of the variance of the difference between the two estimated coefficients and the endpoints of a 95% confidence interval for this difference and summarized in Table: 3.
Consequently, the findings with high p-values suggest that there is a significant difference among the logits over the two set of explanatory variables. Equivalently, the confidence intervals exhibited in Table: 3 for all the explanatory variables include zero and hence concluded that the log odds for Y = 2 is different from the log odds for Y = 1 and Y = 3 is different from the log odds for Y = 2. In practice, if there is any difference in the separate odds ratios over all model covariates then one should consider pooling.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	861.207			
Final	607.876	253.332	30	.000

Pseudo R-Square

Cox and Snell	.117
Nagelkerke	.135
McFadden	.062

Table: 2 Likelihood ratio test for the significance of overall and individual importance of explanatory variables in the model.

Likelihood Ratio Tests

Model with explanatory variable	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	607.876[a]	.000	0	.
x1	609.496	1.620	3	.655

x2	729.706	121.831	9	.000
x3	615.737	7.862	9	.548
x4	787.195	179.319	9	.000

VIII. Conclusion

Logistic regression is a form of regression analysis that is specifically tailored to the situation in which the response variable is dichotomous or polychotomous. Response variable having more than two levels is a situation frequently faced in the categorical data analysis. If the levels of the response variable are nominal scale, nominal multinomial logistic regression is appropriate. Multinomial logistic regression is increasingly common, involving analyses in which the possible causal effects of explanatory variables on a categorical response variable having more than two response categories are assessed via comparison of a series of dichotomous responses. The multinomial logit model is a generalization of dichotomous logit model but complicated in terms of fitting process and interpretation. In case of significant difference is found in the separate odds ratios produced by the different logits over the entire set of explanatory variables, it may be concluded that multinomial logit model adequately fit the data with response variable having more than two levels, otherwise response levels should be pooled into binary levels for ease of computation, mathematical tractability and ease of interpretability. In the current study, there is significant difference among the parameter estimates under different logits and it may be finally concluded that the required multinomial logits model has been established to alleviate poverty in the respect in Bangladesh.

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