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DETERMINANTS OF POVERTY – BINARY LOGIT MODEL WITH INTERACTION TERMS APPROACH

Abstract: The problem of monetary aspect of welfare in employees' household was undertaken in this paper. In order to identify the households in danger of poverty, the binary logit models approach was applied. It was found that the estimation of models without the interaction terms results in misspecification error. Due to this, the interaction terms, between the socio-economic factors of households were included in the model. The obtained results can have significant importance in the aspect of social policy in Poland.

Keywords: poverty, household, logit model, interactions.

1. Introduction

Poverty reduction is a key policy debate in recent literature on social issues. The elaboration of policies for poverty relief requires a thorough knowledge of this phenomenon. Therefore, there is a need for research aimed at the identification of the determinants of poverty and assessing the impact of policies and welfare programs on the poor.

The last two decades have seen considerable analytical efforts in the poverty related literature. There are many studies that emerged to identify the determinants of poverty in recent literature on the problems of social statistics. Since there is no reason to believe that the root causes of poverty are the same everywhere in the world, a country specific analysis is indispensable [Haughton, Khandke 2009].

Literature shows that most of the studies have used household income or expenditure to identify poor households. The most commonly used dependent variables in poverty models are binary indicators. The analysis then proceeds by employing the binary choice model to estimate the probability of a household being poor conditional upon some characteristics.

This study attempts to examine closely the factors that are strongly associated with poverty using binary logit models. The estimation of models is based on the latest Household Budgets Survey data in 2010. The aim of this work is a study of the determinants of poverty among households of the employees. What distinguishes this work is taking into account the interaction terms which play an important role in econometric modeling. They are included in the model in which the effect of one explanatory variable varies according to the levels of another explanatory variable.

2. Poverty measurement

In measuring monetary poverty, there are some issues that need to be considered. These include: defining an indicator of wealth and establishing a minimum acceptable standard of that indicator to separate the poor and the non-poor (usually known as the poverty line).

When estimating monetary measures of poverty, one may have a choice between using disposable income or total expenditure as the indicator of wealth. Some analysts argue that expenditure may better show poverty than income, since the latter may be erratic and fluctuate during the year. On the other hand, some of the issues involved in total expenditure refer to the purchase of durable goods and their maintenance. Therefore, there are some pros and cons in each approach.

In early poverty studies, monetary poverty was measured using expenditure (or income) per capita. Today, in order to compare households of different size and composition, the use of equivalence scales is recommended. The equivalence scale is a tool converting the nominal expenditure (or income) of heterogeneous households in comparable measures of wealth. Applying it to monetary income (or expenditure) of different households gives rise to an equivalised income (or expenditure).[1] In practice, the most commonly used scales in Poland include the OECD scales. The so called original OECD scale (also called the OECD 70/50 scale), assigns a weight of 1 to the first adult, usually the head of the household, a weight of 0.7 to subsequent adults and a weight of 0.5 to children under 15.[2] The so called modified OECD scale states that the first adult should be assigned a value of one, subsequent adults are assigned a value of 0.5 and children 0.3. It should be stressed that for making comparisons between the two scales for measuring poverty in Poland, the original OECD scale is recommended [Dudek 2011; *Poverty*… 2011].

A household is deemed to be poor if its equivalised expenditure (or income) is lower than the accepted line of poverty. Two main forms of monetary poverty lines exist, absolute and relative poverty lines. According to the first of these approaches, the poverty line identifies the amount of money needed to acquire the goods and services that satisfy given absolute minima standards for each of the basic needs. The relative poverty line is a function of the average living standards of the population. A household is poor if it satisfies the needs in a very unacceptable way relative to what is usual in his/her society. Hence, the poverty line is usually established as a proportion of the mean or median income or expenditure of the whole population

[1] I.e. total household income divided by the values of equivalence scale yields an equivalised income.

[2] For example, the value of OECD 70/50 scale for two adults with two small children equals 2.7.

[Rio Group 2006]. The importance or the use of a particular poverty line depends on the purpose and the type of poverty one intends to measure. As in the studies of the Polish Central Statistical Office [*Poverty*… 2011], we use total monthly equivalent expenditure of households measure applying the OECD 70/50 equivalence scale and relative poverty line which equals 50% of the average monthly equivalised consumption expenditure.

3. Methods of analysis – binary choice models approach

This study uses the econometric approach for modeling determinants of poverty in Poland. The variable explained in the model is dichotomous, taking a value of one when the household is poor and a value of zero otherwise. In such cases where Y is a dummy variable, binary choice models should be applied. The main idea behind that model is to find the relationship between the probability (P_i) that Y will take a 1 value and the characteristics of considered individuals. A general class of binary choice models assumes that

$$P_i = P(y_i = 1) = F(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_k x_{ki}) \text{ [Greene 2000]}, \tag{1}$$

where:
P_i – probability, i =1, 2,..., n,
F – a CDF (cumulative distribution function),
β_j – parameters, j = 0, 1, 2,…, k,
x_{ji} – value of explanatory variable X_j for i-th household,
k – number of explanatory variables,
n – sample size.

The two common binary choice models are the binomial logit model and the binomial probit model:

- in logit model: $P_i = \Lambda(\mathbf{x_i^T \beta}) = \dfrac{1}{1+\exp\left(-\mathbf{x_i^T \beta}\right)}$ (2)

- in probit model: $P_i = \Phi(\mathbf{x_i^T \beta}) = \displaystyle\int_{-\infty}^{\mathbf{x_i^T \beta}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt,$ (3)

where: $\mathbf{x_i^T \beta} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki}$.

In the first model F(.) is the logistic CDF denoted by Λ(.), in the second one F(.)=Φ (.) is the standard normal CDF

The explanatory variables have the form of both dichotomy and quantitative variables. It can be shown [Greene 2000] that for quantitative variable X_j holds:

$$\frac{\partial P(y_i = 1|\mathbf{x}_i)}{\partial x_j} = \beta_j f(\mathbf{x_i^T \beta}) \tag{4}$$

where $f(.)$ is the density function that corresponds to the cumulative distribution function $F(.)$. Because the CDF is monotonically increasing in its argument, the second term in the chain rule derivative given in (4) is always positive. As a result, the sign of the parameters always equals the sign of the partial derivative of interest. Moreover, it can be proved that in the logit case, the partial derivatives are given by:

$$\frac{\partial P(y_i = 1 | \mathbf{x}_i)}{\partial x_j} = \beta_j \left(\Lambda(\mathbf{x_i^T \beta}) \cdot (1 - \Lambda(\mathbf{x_i^T \beta})) \right) = \beta_j \cdot P_i \cdot (1 - P_i) \tag{5}$$

where $\Lambda(.)$ is the logistic CDF.

The marginal effect is more complex if interaction terms are included in the model. Applied econometricians typically allow for the interaction term between two independent variables, X_1 and X_2, which is the product $X_1 \cdot X_2$. To illustrate, assume for simplicity that X_1 and X_2 are continuous variables with $P_i = P(y_i = 1) = F(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{1i} \cdot x_{2i})$.

In such case

$$\frac{\partial P(y_i = 1 | \mathbf{x}_i)}{\partial x_{1i}} = \left(\beta_1 + \beta_3 x_{2i} \right) f(\mathbf{x_i^T \beta}) \text{ and } \frac{\partial P(y_i = 1 | \mathbf{x}_i)}{\partial x_{2i}} = \left(\beta_2 + \beta_3 x_{1i} \right) f(\mathbf{x_i^T \beta}). \tag{6}$$

The logistic distribution and the standard normal are quite similar, other than in the tails. As a result, the two models give similar results, except in cases where a sample in which the proportion $y_i = 1$ (or the proportion $y_i = 0$) is very small [Baum 2006].

The logit model has an advantage over the probit model – the effects of changes in explanatory variables can be interpreted in terms of odds ratios. Odds are defined as the ratio of two probabilities P_i and $1 - P_i$, i.e. the ratio of the probability of occurrence of an event to that of nonoccurrence.[3] For the logit model odds equal $\exp(\mathbf{x_i^T \beta})$, because

$$Odds = \frac{P_i}{1 - P_i} = \frac{\left(\dfrac{1}{1 + \exp\left(-\mathbf{x_i^T \beta}\right)} \right)}{\left(\dfrac{\exp\left(-\mathbf{x_i^T \beta}\right)}{1 + \exp\left(-\mathbf{x_i^T \beta}\right)} \right)} = \exp(\mathbf{x_i^T \beta}). \tag{7}$$

The exponential relationship provides an interpretation of the odds ratio (OR). For a unit change in X_j, the odds are expected to change by a factor of $\exp(\hat{a}_j)$, holding all other variables constant.

[3] For instance, when P(y = 1) = 0.75; the odds equals 0.75/0.25 = 3.0; meaning that being poor is three times as likely as not being poor.

$$OR_j = \frac{Odds\ \ for\ (X_j + 1)}{Odds\ \ for\ (X_j)} = \\ = \frac{\exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_j \left(x_{ji} + 1\right) \ldots + \beta_k x_{ki})}{\exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_j x_{ji} \ldots + \beta_k x_{ki})} = \exp(\beta_j). \tag{8}$$

To illustrate a case in which interaction terms are included in model, as before, assume for simplicity that $P_i = P(y_i = 1) = F(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{1i} \cdot x_{2i})$

$$OR_1 = \frac{Odds\ \ for\ (X_1 + 1)}{Odds\ \ for\ (X_1)} = \exp(\beta_1 + \beta_3 x_{2i}) \tag{9}$$

and

$$OR_2 = \frac{Odds\ \ for\ (X_2 + 1)}{Odds\ \ for\ (X_2)} = \exp(\beta_2 + \beta_3 x_{1i}). \tag{10}$$

Thus, in the presence of the interaction term, the odds ratio for the variable of interest has to be determined at a predefined level of the interacting variable. In particular, if there is the interaction between two dichotomous predictors, the estimated parameters for the main effects and the interaction term have straightforward interpretations. The coefficient for each main effect represents the effect of that variable in observations in which the other variable is absent [Hilbe 2009].

The parameters of the logit model are usually estimated by the maximum likelihood method (ML). Most modern statistical packages have established routines to estimate parameters by this method. They also facilitate testing hypotheses about parameters and report goodness of fit measures, often called R-square statistics. The most often used are *pseudo-R-square* and *count R-square* measures. Because these statistics do not mean what *R*-square means in a conventional regression, some researchers suggest interpreting this statistic with great caution. It should be emphasized that in binary choice models goodness of fit measures are of secondary importance. What matters are the expected signs of the slope parameters in the model and their statistical and practical significance [Gujarati 2011].

The logit models are used to indicate the household's attributes correlated with the high risk of being poor. To compare alternative models, the Akaike (AIC) and the Bayesian (BIC) information criteria are used [Cameron, Trivedi 2005; Hardin, Hilbe 2007].

To assess if all the relevant explanatory variables are included in the model, some tests may be applied. For example, in Stata Statistical Software, the *linktest* command provides a means of detecting an inadequacy of the relationship between outcome and predictors. The idea behind that test is that if the model is properly specified, one should not be able to find any additional predictors that are statistically significant except by chance. *Linktest* uses the predicted value and its square as the predictors to rebuild the model. Unless the model is completely misspecified, the predictor variable should be statistically significant, but not its square. If the latter is significant, then the *linktest* fails. This usually means that either relevant variables are omitted, or the considered functional form is inadequate. In our opinion, such an approach can be used to assess whether all the important interaction terms are included in the model.

4. Binary choice models in poverty analysis − literature review

Pioneering work in the application of binary choice models in the analysis of poverty is presented in the article [Phipps 1991]. In that study, concerning the situation in Canada, the dependent variable was a dummy variable equaled to one if the household's gross income was below the poverty level and set equaled to zero otherwise. Other research about the determinants of poverty by using binary choice models includes: [Grootaert 1997; Seeth et al. 1998; Elmelech, Lu 2004; Coromaldi, Zoli 2012]. With regard to the data of Polish households, the probit models were used by Szulc [1998; 2000; 2006] and Panek [2000-2011]. Moreover, the logit models in poverty analysis were applied i.a. in studies [Okrasa 1999; Dudek 2006; Kasprzyk, Fura 2011; Rusnak 2012].

There are many attempts in the literature to identify the determinants of poverty (see for example [Panek 1991; Phipps 1991; Rusnak 2012] and others).

Generally, studies on poverty indicate that the potential explanatory variables of poverty can concern the economic, demographic and human capital attributes of the household. There are both continuous variables and dummy variables here. The set of economic determinants include, for instance, occupation and employment status. Demographic variables are usually captured by the age of the household head, age squared, gender of the household head and marital status. The age variable and the age squared variable deal with the stage in the life cycle of a household. The human capital variable can be captured by the education variable.

In order to indicate poverty determinants in the considered group of households AIC and BIC information criteria were applied.

5. The data

The data are drawn from the Household Budget Survey (HBS) carried out by the Central Statistical Office [*Household*… 2011]. The HBS plays an important role in the analysis of living standards of the population. It is the basic source of information on the incomes, expenditure, demographic and socioeconomic characteristics of households.

The study focuses on the households of the employed' − i.e. such households whose exclusive or prevailing source of livelihood is income from employment in either the public or private sector. It encompasses 18441 such households in 2010. The basic information about the analyzed sample is presented in Table 1.

Table 1. The structures of households in regard to the their basic characteristics

Households of the employed:	Percentage of households [%]	
	poor (Y = 1)	not poor (Y = 0)
Labor position		
BCW (blue-collar worker)	22.93	77.07
WCW (white-collar worker)	5.62	94.38
Education level of the reference person		
Educ_3 (Tertiary education)	2.75	97.25
Educ_2 (Secondary)	16.96	83.04
Educ_1 (Other)	34.52	65.48
Class of locality		
KLM_1 (Cities)	6.70	93.30
KLM_2 (Medium towns)	10.38	89.62
KLM_3 (Small towns)	16.50	83.50
KLM_4 (Villages)	22.49	77.51
Regions		
R_C (Central Region)	9.92	90.08
R_S (South Region)	13.35	86.65
R_E (East Region)	21.18	78.82
R_N-W (North-West Region)	15.32	84.68
R_S-W (South-West Region)	13.72	86.38
R_N (North Region)	17.68	82.22

Source: own calculations based on the HBS data.

The household is considered as poor if its monthly equivalent expenditure is lower than the poverty line, assumed to be 651 zlotys. In Table 1 the following attributes of the reference person (household head) and whole household are taken into account.

1. Labor position represented by dummy variables:

- BCW (blue-collar worker) in the case of manual labor positions,
- WCW (white-collar worker) in the case of non-manual labor positions.

2. Education level of the reference person represented by dummy variables:

- Educ_3 denoting tertiary (higher) education of the reference person,
- Educ_2 referring to the case if the reference person reports a secondary or post-secondary level of education,
- Educ_1 denoting situation if the reference person has basic vocational, lower secondary, primary or no formal education.

3. Class of locality:

- KLM_1 stands for cities with a population of at least 100 thousand inhabitants,
- KLM_2 denotes medium towns with less than 100 thousand inhabitants and at least 20 100 thousand,
- KLM_3 stands for small towns with less than 20 thousand inhabitants,
- KLM_4 denotes villages.

4. Region of residence:

- R_C denotes the Central Region including the łódzkie and mazowieckie voivodeships,
- R_S stands for the South Region including the małopolskie and śląskie voivodeships,
- R_E denotes the East Region including the lubelskie, podkarpackie, świętokrzyskie, and podlaskie voivodeships,
- R_N-W stands for the North-West Region including the wielkopolskie, zachodniopomorskie, and lubuskie voivodeships,
- R_S-W denotes the South-West Region including the dolnośląskie and opolskie voivodeships,
- R_N stands for the North Region including the kujawsko-pomorskie, warmińsko-mazurskie, and pomorskie voivodeships.

Moreover, other potential explanatory variables are considered: the number of unemployed and disabled people in a household, the age of the reference person, the size of the household (the number of people in the household), female headed household, the number of children under 15 in the household.

6. Results

At the first stage we considered potential variables that can explain the differentiation in the financial status of households. We took into account many attributes of the household head and characteristics referring to the whole household. In the next stage we continued in accordance with statistical criteria recommended in literature [Cameron, Trivedi 2005; Hardin, Hilbe 2007].

We estimated a number of models explaining being poor. The parameters of the logit models are estimated using Stata Statistical Software v.11. The selection of variables was influenced by substantive and statistical considerations. To compare models with a different set of explanatory variables we used the Akaike and the Bayesian information criteria. Moreover, the *linktest* approach was applied. The failure of this test pointed to the need to include additional interaction terms. Finally, we obtained a model[4], for which the results are presented in Table 2.

[4] Fitting models without the interaction terms causes significant *linktest* results. For the model presented in Table 2 we obtain the following values of goodness of fit measures: *pseudo*-R^2 = 0.191 and *count* R^2 = 0.856.

Table 2. Results of the estimation of the binary logit model

Variable	Estimated parameter	Standard error of parameters	Z statistics	Odds ratio	Standard error of odds ratio
Educ_2	–1.498	0.232	–6.450	0.224	0.052
Educ _3	–4.771	0.816	–5.850	0.008	0.007
KLM_1	–1.927	0.401	–4.800	0.146	0.058
KLM_2	–0.703	0.143	–4.930	0.495	0.071
Size	0.288	0.038	7.580	1.333	0.051
AgeHH	–0.023	0.003	–8.780	0.978	0.003
Female	0.393	0.053	7.370	1.481	0.079
R_C	–0.163	0.067	–2.440	0.850	0.057
R_E	0.431	0.060	7.170	1.539	0.093
R_N	0.324	0.065	4.980	1.383	0.090
Unemployed	0.760	0.079	9.570	2.138	0.170
Educ _3*Size	1.295	0.386	3.350	3.651	1.411
Educ _3*Size2	–0.122	0.045	–2.730	0.885	0.040
KLM_1*Size	0.516	0.189	2.730	1.676	0.317
KLM_1*Size2	–0.048	0.022	–2.170	0.953	0.021
Educ _2*Size	0.326	0.088	3.710	1.385	0.122
Educ _2*Size2	–0.027	0.009	–3.160	0.973	0.008
AgeHH*BCW	0.018	0.002	10.770	1.018	0.002
Child_4*Unemployed	1.631	0.826	1.970	5.108	4.220
Size2*Child_4	0.009	0.004	2.360	1.009	0.004
BCW*KLM_1	0.325	0.143	2.280	1.385	0.197
BCW*KLM_2	0.347	0.161	2.160	1.415	0.228
Size2*Unemployed	–0.007	0.003	–2.280	0.993	0.003
Constant	–1.720	0.200	–8.740	–	–

Source: own calculations made in the Stata v. 11.

Most of the variable names appearing in Table 2 are explained in the previous section. Moreover, “Size” denotes the number of people in the household, “Size2” – its square, “AgeHH” – the age of the household head (reference person), “Female” – female headed household, “Unemployed” – the number of unemployed people in the household, “Child_4” refers to households with four or more children.

In order to verify the validity of our model presented in Table 2 we apply the *linktest*. We find that at 0.05 level of significance there is no reason to reject the null hypothesis that there is no evidence of misspecification.[5]

[5] This is probably not the only model with interaction terms which has such property. Due to a very large number of possible interactions we did not examined all models.

Some important results can be derived under the *ceteris paribus* assumption. The probability of being poor:

- is bigger for households whose reference person is a women than in the case of a man;
- is lower in the Central Region and bigger in the East and North Regions than the South, South-West and North-West Regions;
- is dependent on the interaction of household size with other characteristics such as the level of education of the household head, the class of locality, the number of unemployed persons in the household and having at least 4 children under 15.

The first of these results is consistent with those presented in [Szulc 2000] and the second one is similar to the findings of Rusnak [2012]. It is difficult to compare with other studies the impact of household size on poverty. This is due to taking into account the interaction terms in this research. According to formula (6), a sign of the marginal effect for household size is computed from the following expression:

$$\begin{pmatrix} 0.288+1.295Educ\_3-0.244Educ\_3\cdot \text{Size} \\ +0.326Educ\_2-0.054Educ\_2\cdot \text{Size}+0.516\text{KLM\_1}-0.096\text{KLM\_1}\cdot \text{Size} \\ +0.018Child\_4\cdot \text{Size}-0.014\text{Unemployed}\cdot \text{Size} \end{pmatrix}.$$

It can be positive (i.e. for households of a single unemployed person living in cities – regardless of education level) or negative (i.e. for households composed of 4 adults and 3 children living in cities, without the unemployed, with a reference person that acquired tertiary education).

The risk of poverty is lower for households whose reference person is a white-collar worker than in the case of blue-collar workers. The odds ratio in this case also depends on the class of locality and the age of the reference person. For example, it equals 3.048 if the household head is 45 and lives in a city (i.e. exp(0.018 × 45 + 0.325). This means that among households headed by a person aged 45 living in cities, the odds of being poor are about 3 times higher for blue-collar workers than for white-collar workers.

Falling into the sphere of poverty is bigger for households in the countryside or in small towns than in the case of households from big towns and cities. The corresponding odds ratios are dependent on household size and labor position, e.g. if a household of a blue-collar worker consists of 4 people, then the odds of being poor is about 26.6% less for inhabitants of cities than for ones living in small towns or villages (i.e. exp (–1.927 + 0.516 × 4–0.048 × 16 + 0,325) = 0.734 and 1–0.734 = 0.266).

As expected, the probability of being poor decreases – under the *ceteris paribus* assumption – with the increasing level of education of the household head. The strength of dependence is correlated with the size of the household. For example, the odds ratio of falling into the sphere of poverty for higher education equals 0.213 for households consisting of 4 people (i.e. exp(–4.771 + 1.295× 4–0.122 × 16) = 0.213).

The increase in the number of unemployed persons in the household is more likely to result in falling into the class of poverty. The corresponding odds ratios depend on the size of household and the number of children below 15, e.g. for households consisting of 8 people having 4 small children equals 7 (i.e. exp (0.760 + 1.631 – 0,007 × 8^2) = 7.099). This means that in such cases each additional person unemployed increases the odds of being poor by about 7 times.

7. Summary

This study examined the influence of some variables on poverty among the households of the employed in Poland. The analysis that the variables that are positively correlated with the probability of being poor are the size of the household, living in a rural area, working in manual positions. The variables that are negatively correlated with the probability of being poor are: having at least secondary education, residing in cities or medium towns in the central region.

The interactions of economic and social determinants of poverty must be researched as strong inter-linkages exist. A clearer definition of what constitutes a poor household is warranted both for research and targeting purposes.

Finally, we can state that binary choice models are useful tools for analytical, policy-making and for monitoring purposes. They enable understanding the factors determining poverty and the identification of vulnerable groups of households. The results obtained should be used in the creation of an effective social policy.

Short-term policies against poverty should include direct assistance to poor households. On the other hand, long-term policies should concentrate on such areas as raising the level of education among the poor, rural development and decreasing under-employment. To better help policy makers in designing policies favouring the poor, further research is needed. Suggestions for future studies include the understanding of poverty dynamics and the persistence of poverty. For such analysis the availability of panel data is required. Panel data analysis can provide insights into the effects of anti-poverty policies and the political changes in households over time. In particular, it might assess the impact of various transfer and taxation policies on the situation of households at risk of poverty.

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DETERMINANTY UBÓSTWA – PODEJŚCIE WYKORZYSTUJĄCE BINARNE MODELE LOGITOWE Z INTERAKCJAMI

Streszczenie: W ujęciu klasycznym identyfikacja sfery ubóstwa dokonywana jest wyłącznie ze względu na sytuację dochodową gospodarstw domowych. W pracy podjęto problem identyfikacji gospodarstw domowych zagrożonych ubóstwem za pomocą binarnych logitowych modeli ubóstwa. Stwierdzono, że estymacja modeli bez interakcji powoduje błędy specyfikacji. Dlatego też do modelu włączono interakcje między cechami społeczno-ekonomicznymi gospodarstw domowych. Uzyskane wyniki mogą mieć istotne znaczenie w aspekcie polityki społecznej w Polsce.

Słowa kluczowe: ubóstwo, gospodarstwo domowe, model logitowy, interakcje.