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A Comparison of the Models Over the Data on the Interest Level in Politics in Turkey and Countries that are Members of the European Union: Multinomial or Ordered Logit Model?

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Abstract: This study focuses on the comparison of the choice based multinomial logit model and status based ordered logit model, which are widely used when the dependent variable is categorical with more than two levels. To do this, a survey data is used on the interest of individuals in politics in Turkey and ten countries that are members of the European Union. After determining the true model, it is clarified that the interest of individuals living in countries that are members of the European Union in politics remarkably differs from that of in Turkey. Additionally, significant individual characteristics on the tendency to politics are also given along with their marginal effect on the relative risk ratios.

Keywords: IIA assumption, ınterest in politics, multinomial logit model, ordered logit model, parallel slopes assumption

INTRODUCTION

It is an important phase to determine whether Multinomial Logit Model (MLM) or Ordered Logit Model (OLM), commonly used in modelling in case that dependent variable is multi-category, is more convenient for the data structure. MLM is a choice based model and it is of initial condition that the dependent variable has been measured with nominal scale. On the other hand, OLM is a status based model and it requires a significantly distinct ordering between the dependent variable levels. However, in some cases, it might be difficult to decide whether the dependent variable is precisely choice based or status based. While working with such data, it is of primary importance to clarify which model represents the data more accurately.

In the study of Peng and Nichols (2003), dependent variable that measures the risk level of students was categorized as High Risk, Medium Risk and Low Risk. The level of adolescent behavioral risk was modelled by MLM. However, when we carefully examined the variable type, it could also be assesed as an ordinal variable and thus it could have been modelled by OLM.

Ascough *et al*. (2002) analysed the computer usage and gratification via OLM. Dependent variable that states the frequency of computer usage was taken as an ordered variable. However, computer usage also specifies a choice throughout the categories of the dependent variable and the data could have been modelled by MLM.

Klaeboe (1999) wanted to model the reactions of peope who were exposed to environmental damage and used OLM in the study. Dependent varible is the reaction level of people with categories beginning from highly reactive to the lower degree of reaction. Here, MLM could also be thought as an alternative model to OLM.

O'Donnell and Connor (1996) compared the ordered logit and probit model specifications in their study using the data on the severity of damage as a function of the driver attitudes. Similar to the studies mentioned above, dependent variable could be evaluated as a choice based variable and could be modelled by MLM.

In summary, we have realized that in many studies using OLM or MLM in the literature, the choice is made without examining the data type, accurately. However, the true model should be determined after testing the validity of required model assumptions. Otherwise, obtained results and interpretations could be misleading.

In this study, the conditions and suggestions that could answer the question MLM or OLM? are given in detail. For that purpose, the data of the study entitled ESS4-2008, ed.4.0, which was performed by the European Social Survey (ESS) during 2008-2009, were used. In this study which researched how the interest levels (Very interested-Quite interested-Hardly interested-Not at all interested) of individuals in politics change according to various personal characteristics and countries, it is observed that the dependent variable reflects both the choice of individuals and the present condition. In that case, it gets difficult to make a beforehand decision about the accurate model only by considering the structure of the dependent variable.

In this -study, for the purpose of determining the most convenient model for the data structure, the data were modelled, respectively with MLM and OLM in the

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Table 1: Some popular models used for modelling the polychotomous dependent variable

Model	Type of the dependent variable	Model assumptions
Multinomial logit	Nominal	•Only the characteristics of individuals are required. •Strict assumption of Independence of Irrelevant Alternative (IIA) has to be satisfied.
Multinomial probit	Nominal	•Only the characteristics of indivuduals are required. •No other assumption is necessary including IIA.
Ordered logit	Ordered	•Only the characteristics of indivuduals are required. •Parallel Slopes Assumtion (PSA) is required.
Ordered probit	Ordered	•Only the characteristics of indivuduals are required. •Parallel Slopes Assumtion (PSA) is required.
Nested logit	Nested nominal design	•Inclusive Value (IV) are required to be positive.
Conditional	logitNominal	•Characteristics of the choice and individuals are both required.

*: Logit and Probit models only make difference from the link function they used

first phase and model assumptions were tested. Additionally, whether the dependent variable was ordered in OLM as it was considered to be was statistically tested. Determining the accurate model for the data structure, detailed comments of the results were included in the last phase.

METHODOLOGY

The models that represent the behaviour of the dependent variable, consumer or decision maker are called preferred models. Alternatives such as the decision of buying or not buying a house, becoming or not becoming indebted are among the examples to be given for preferred models. Dependent variables used in these models can be divided into three main groups:

- Binary (dummy or dichotomous) variables
- Polychotomous variables
- Limited variables

Dichotomous variables are coded as 0 or 1 and analysed within the scope of Linear Probability Model, Two-level Logit and Probit models. On the other hand, polychotomous variables are coded as (0, 1, 2…) or (1, 2, 3…) and analysed by taking the conditions given with Table 1 into consideration.

Finally, limited variables are divided into two as follows: censored and truncated variables. Such variables are modelled with the approaches of Duration Models and Tobit Model.

In this study, since MLM and OLM are compared via a real data set that is thought to be modelled with both of the models, the theoretical structure of these models is given below.

Multinomial logit model: The case that the dependent variable has J pieces of level is an expansion of the non-linear features that are developed in case that the dependent variable has two levels in the logit model. One of the levels of the dependent variable is selected as base and that level is generally showed as the J. level. J. level is compared with other levels of the dependent variable by twos. While each level of the dependent variable is considered to be two-level, the formation of a model related with the J. level is avoided, which is generally taken as a reference due to the fact that the total of probabilities obtained from each model for the observation i. shall necessarily be equal to 1. In this case, a total of J-1 model equation is estimated. Considering that there are K pieces of explanatory variables including the constant term, the total number of estimating parameters is $K(J-1)$. In case that logit link function is selected as the non-linear transformation for the data, the model is called multinomial logit model and model equations are defined as follows.

$$\log\left[P(Y_i = j)/P(Y_i = J)\right] = \sum_{k=1}^{K} \hat{b}_{jk} x_{ik} = Z_{ij}\,;\, j \neq J = 1,2,\ldots,J-1 \quad (1)$$

The probability that observation i. is equal to the j. level of the dependent variable is as follows:

$$P(Y_i = j) = [exp\,(zij)][P(Y_i = J)\,;\, j = 1, 2, \ldots J-1 \quad (2)$$

This equation could be solved in case that the probabilty of $P(Y_i = J)$ is known. The total of probabilities obtained from J pieces of equations shall be equal to 1 for the observation i. and this feature is given with Eq. (3):

$$\sum_{i=1}^{J} P(Y_i = J) = 1 \quad (3)$$

Considering the Eq. (2) and (3), the probability of $P(Y_i = J)$ is obtained as follows:

$$P(Y_i = J) = 1 - \sum_{j=1}^{J-1} P(Y_i = j) = 1 - \sum_{j=1}^{J-1} \exp(Z_{ij}).\, P(Y_i = J) \quad (4)$$

$$P(Y_i = J) + P(Y_i = J) \sum_{j=1}^{J-1} \exp(Z_{ij}) = 1 \Rightarrow P(Y_i = J)$$
$$\left[1 + \sum_{j=1}^{J-1} \exp(Z_{ij})\right] = 1 \quad (5)$$

$$P(Y_i = J) + P(Y_i = J) = \frac{1}{1 + \sum_{j=1}^{J-1} \exp(Z_{ij})} \quad (6)$$

When the Eq. (6) is replaced with Eq. (2), the following probability equation is obtained:

$$P(Y_i = J) = P_{ij} = \exp(Z_{ij}) / \left[1 + \sum_{j=1}^{J-1} \exp(Z_{ij})\right]; j = 1,2,\ldots,J-1 \quad (7)$$

As in the case that the dependent variable has two levels, obtaining J-1 pieces of equations is adequate in case that the dependent variable has more than two levels, due to the condition that the total of probabilities is 1. Since no equation is obtained for the J. level of the dependent variable that is selected as base, the parameter estimations $(\hat{b}_{JK}, k = 1,2,\ldots K,)$ related with this level shall be 0. If this feature is used for the simplification of the Eq. (7), the following equation is obtained:

$$P(Y_i = j) = exp\,(Z_{ij})/D$$

$$D = \sum_{j=1}^{K}\left[\exp\left(Z_{ij}\right)\right]; j = 1,2,\ldots,J \quad (8)$$

In this case, it is concluded that the expression $D_1 = 1 + \sum_{j=1}^{J-1}\left[\exp(Z_{ij})\right]$ is equal to the expression- $D_2 = \sum_{j=1}^{J-1}\left[\exp(Z_{ij})\right]$.

Since no model was set in relation with the J. level of the dependent variable, the parameter estimations of this level will be 0 (for $\hat{b}_{jk}; k = 1,2,\ldots K$), as it is already stated. Owing to the fact that the last term of the equation D_2 will be equal to 1, the equations of both D_1 and D_2 express the very same thing. In this case, each of the observation n will be included in one of the J categories with the probabilities given with Eq. (8). The probabilities P_{ij}(j = 1, 2, ..., J – 1) and P_{iJ} related with the observation of X_i are obtained by replacing X_i with X respectively in Eq. (8) and (6) for the observation i. as explanatory variable values. Non-functional variables set could be defined as follows for the model:

$$\begin{cases} y_{ij} = 1\ ;\ \textit{if observation i is in category } j \\ y_{ij} = 0\ ;\ \textit{otherwise.} \end{cases}$$

A practical approach to observe the behaviours of multi-category probabilities is to focus on the ratios, in other words odds of probabilities rather than the probabilty itself. The odds from the Eq. (8) is given as follows for the incident of $Y = j$, which is related with $Y = j^{t}$:

$$\frac{P(Y = j)}{P(Y = j')} = \frac{\exp(\sum \hat{b}_{jk} x_k) / D}{\exp(\sum \hat{b}_{j^t k} x_k) / D} = \exp\left[\sum (\hat{b}_{jk} - \hat{b}_{j^t k}) x_k\right] \quad (9)$$

Here the purpose is to reveal how the behaviour of the odds of the dependent variable levels that are dealt together with the change in the explanatory variable that is dealt when other explanatory variables is immobilized in the model change. Since the function Exp(.) shows increase as the expression within it expands, the sign of the difference between two coefficients indicates the change direction of odds as the explanatory variables change. Odds, odds-ratios and marginal effects are used during the interpretation of multinomial models. In MLM, the odds ratio that is expressed with Eq. (9) is not affected by the presence of a third alternative, in other words, it gets independent from other alternatives.

Assumption of Independence of Irrelevant Alternatives (IIA): MLM is based on the assumption of IIA. This assumption indicates that adding an alternative to the model or changing the feature of a model that is present in the model does not change the odds between the alternatives j and j' and it is based on the assumption that the error term is independent and homoscedastic. The most important limitation in MLM is related with the assumption that the error term is independent throughout the selections. The violation of this assumption emerges when the observations assess both of the alternatives similarly or equally. The relative odds between two alternatives is dependent on the characteristics of some observations that are selected specifically for two alternatives and thus, it is independent from the nature and number of all other alternatives that are simultaneously taken into consideration. Considering two alternative levels of the dependent variable such as j and j', it is revealed that the odds between these alternatives are only the functions of parameters and consequently, they are not affected by the parameters related with other alternatives.

The validity of this assumption is tested through using the test developed by Hausman and McFadden (1984). This test is also a guideway to degrade two or more categories into a single category. In other words, if the individuals prefer two categories for one another, related categories could be combined or the alternative category could be excluded from the model as a result of this test. Hausman-McFadden test initially starts with the estimation of the model, which includes all categories of the dependent variable. And then including the same

explanatory variables set in the model, parameter estimations are obtained for the model that is limited by exclusion from one or more selection models. The fact that parameter estimations that are obtained for the limited and unlimited model show similarity indicates that the feature of IIA is provided. The Hausman-McFadden test statistics, which test the hypothesis that is established respectively as:

$H_0: \hat{\beta}_u = \hat{\beta}_r$ (assumption IIA is valid)

$H_1: \hat{\beta}_u \neq \hat{\beta}_r$ (assumption IIA is invalid)

in such a way that $\hat{\beta}_u$ and β_r indicate the parameter estimations obtained from the limited and unlimited model and covariance matrices of estimations V_u and V_r, is given below:

$$q = \left[\hat{\beta}_u - \hat{\beta}_r\right]\left[V_r - V_u\right]^{-1}\left[\hat{\beta}_u - \hat{\beta}_r\right] \tag{10}$$

This statistics have a chi-square distribution with the degrees of freedom that is equal to the difference between the parameter numbers in both of the models (Powers and Xie, 2000).

Ordered logit model: Another method that is developed in case that the dependent variable has more than two categories is OLM. While the levels are unordered in MLM, there is a certain ordering between the levels in OLM. This ordered nature of the dependent variable levels does not indicate the difference of powers of categories according to one another. In other words, coding is performed only for the purpose of entitling the dependent variable levels in a certain order. Namely, it does not mean that the answer related with $Y_i = 2$ is two times stronger than the answer related with $Y_i = 1$.

Due to the non-separable nature of the dependent variable, data that is measured with an ordinal scale can not easily be modelled with the classical regression. Another alternative to be taken into consideration here is MLM. However, such models fail since they do not consider the ordered structure of the dependent variable and consequently do not use the available information fully Liao (1994).

In case that an obscurity is encountered regarding whether the dependent variable is ordered or not, it will be significant to accept the fact that the dependent variable is not ordered and the data will be modelled with MLM. Accepting the dependent variable as ordered although it is indeed unordered makes the person accept an ordering that is not possessed regarding the results and it requires an assumption of "parallel slopes" that could lead to the obtainment of non-objective parameter estimations. On the other hand, accepting the dependent variable as unordered although it is indeed ordered indicates the negligence of an ordering between the dependent variable levels. While this negligence might cause an efficiency loss, it is not possible for such kind of an error to affect the estimations and cause non-objective estimations. Comparing these two probable mistakes, it is seen that efficiency loss is a less important error that is made according to non-objective estimations (Borooah, 2002).

The model is a natural expansion of two-level probability models that are set with the approach of latent variable (Liao, 1994). As it is already defined, the latent regression model is given below:

$$Y^* = \sum_{k=1}^{K} \hat{b}_k X_k + \varepsilon \tag{11}$$

The latent varible Y^* can not be observed and is considered to be the undercurrent of the observed incident. It is assumed that the error term e shows a certain symmetrical distribution with a mean of 0 as normal or logistic. For the ordered logit model, e (error term) has a logistic distribution with a mean of 0 and a variance of $p^2 / 3$.

Considering that the dependent variable has J pieces of ordered categories, the relation between the observed levels and slopes could be given as follows:

$$\begin{aligned} &Y_i = 1, && Y^* \leq \mu_1 (=0) \\ &Y_i = 2, && \mu_1 < Y^* \leq \mu_2 \\ &Y_i = 3, && \mu_2 < Y^* \leq \mu_3 \text{ ; } i = 1, 2, ..., N \\ &Y_i = J, && \mu_{J-1} < Y^* \end{aligned} \tag{12}$$

The μ 's in Eq. (12) are the unknown threshold parameters that separate the adjoining categories. In other words, they indicate after which values of the latent variable (Y^*) the observations change mind and direct towards other choices coded in the dependent variable. In general, the probabilities for the dependent variable models having ordered categories are expressed by using the approach of latent variable, as follows:

$$\begin{aligned} P(y = j \mid x_k) = {} & F\left[\mu_j - \sum_{k=1}^{K} \hat{b}_k x_k\right] \\ & - F\left[\mu_{j-1} - \sum_{k=1}^{K} \hat{b}_k x_k\right] \end{aligned} \tag{13}$$

Here the F shows the distribution function that is assumed for the error term. Equation (13) gives the general form of the probability that the observed y could be included in category j. and the μ 's and b's are estimated with the ordered logit model. The constraint $\mu_1 < \mu_2 < \mu_3 < ... < \mu_{J-1}$ shall be provided for all of the probabilities to be positive. The latent variable Y^* shall be

separated in such a way to form an area of J pieces for a J-category- dependent variable and J-1 pieces of threshold parameters are required for the constitution of an area of J pieces. In case that the model includes a constant term, one of the threshold parameters can not be estimated. In this respect, it is suggested by Greene (2000) that the first threshold parameter (μ_1) is normalized to 0. Under these circumstances, the estimation of totally *J–2* pieces of threshold parameters is required in the model that includes a dependent variable with J-ranked-category. Since the first threshold parameter is 0, all of the estimated threshold parameters shall be positive and there is the relation of $O<\mu_2 < \mu_3 < ... < \mu_{J-1}$ between them (Liao, 1994).

The probability that the dependent variable of any observation is included in j. and lower categories is given with the following equation in general:

$$\begin{aligned} P(y \le j) &= P(y^* \le \mu_j) = P(\sum_{k=1}^{K} \hat{b}_k x_k + u_i \le u_j) \\ &= P(u_i \le \mu_j - \sum_{k=1}^{K} \hat{b}_k x_k) \\ &= F(\mu_j - \sum_{k=1}^{K} \hat{b}_k x_k) \end{aligned} \tag{14}$$

In order to assess the model quality in OLM, Correct Classification Rate (CCR) is computed. However, the cut-off value is not 0.5 here anymore. While assigning the observations to groups, the latent variable Y^* is used. The observed *Y* values are already present in the data for each observation. The expected values, on the other hand, are obtained through Y^*, which is a liner combination of the parameters that are estimated from the model and explanatory variables:

$$Y_i^* = \sum \hat{b}_k x_{ik} \tag{15}$$

For each observation, the explanatory variable values and parameter estimations are present in the *undercurrent index*, which is estimated from the model by being substituted in the equation above. The estimated level is determined for the observation by considering between which threshold parameters this obtained value is included. Following these estimations related with all of the observations, CCR table is obtained for the model by forming a crosswise table for values that are estimated from the observed *Y* values and the model.

Probability equations, which are related with the OLM that is also known as proportional-odds models and obtained in case that the link function is selected in a logit way, are given below for the condition in which the dependent variable has J peices of ordered categories.

$$\log\left[\frac{P(y \le j \setminus x)}{1 - P(y \le j \setminus x)}\right] = \mu_j \sum_{k=1}^{K} \hat{b}_k x_k ; j = 1,2,... J-1 \tag{16}$$

The left side of Eq. (16) is called cumulative logit (Liao, 1994). The expression of Eq. (16) as probability, which is called logistic regression, is given with Eq. (17):

$$P(y \le j) = P(y^* \le \mu_j) = \frac{e^{\mu j - \sum_{k=1}^{K} \hat{b}_k x_k}}{1 + e^{\mu j - \sum_{k=1}^{K} \hat{b}_k x_k}} \tag{17}$$

Considering that the total of probabilities obtained from all of the categories of observation-related dependent variable is 1, it is not required to estimate the probability that it is included in the last category of the dependent variable. When Ψ that shows a special logistic distribution is written instead of F in the expression given with Eq. (13), the OLM model given with Eq. (18) is obtained. Probability equations for the model are as follows:

$$P(y = 1)\psi\left[\sum_{k=1}^{K} \hat{b}_k x_k\right] = \frac{\exp\left(-\sum_{k=1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(-\sum_{k=1}^{K} \hat{b}_k x_k\right)} \tag{18}$$

$$\begin{aligned} &P(y = 2)\psi\left[\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right] - \psi\left[-\sum_{k-1}^{K} \hat{b}_k x_k\right] \\ &= \left\{\frac{\exp\left(\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}\right\} - \left\{\frac{\exp\left(-\sum_{k-1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(-\sum_{k-1}^{K} \hat{b}_k x_k\right)}\right\} \end{aligned} \tag{19}$$

$$\begin{aligned} &P(y = 3)\psi\left[\mu_3 - \sum_{k-1}^{K} \hat{b}_k x_k\right] - \psi\left[\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right] \\ &= \left\{\frac{\exp\left(\mu_3 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(\mu_3 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}\right\} - \left\{\frac{\exp\left(\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(\mu_2 - \sum_{k-1}^{K} \hat{b}_k x_k\right)}\right\} \end{aligned} \tag{20}$$

$$\begin{aligned} &P(y = J) = 1 - \psi\left[\mu_{J-1} - \sum_{k=1}^{K} \hat{b}_k x_k\right] \\ &= 1 - \left\{\frac{\exp\left(\mu_{J-1} - \sum_{k=1}^{K} \hat{b}_k x_k\right)}{1 + \exp\left(\mu_{J-1} - \sum_{k=1}^{K} \hat{b}_k x_k\right)}\right\} \end{aligned} \tag{21}$$

Parallel slopes assumption: The basic assumption of OLM is the parallel slopes assumption. This assumption

indicates that coefficients ($\hat{b}_k$ s) that connect the variable values with different categories shall be the same throughout all of the categories for an explanatory variable, which affects the probability that an individual might be in ordered categories. In other words, as in MLM, there is no need to form J-1 pieces of models separately for a dependent variable having J pieces of levels and it is assumed that any explanatory variable has the same parameter estimation for all of the levels. Equations differ only in their constants for each category.

The validity of the parallel slopes assumption is tested through the estimation of MLM on the data. MLM enables the slope coefficients to differ for J pieces of categories of the dependent variable. While the OLM estimates the total K pieces of coefficients including the constant, MLM gives the parameter estimation of $K(J-1)$.

Regarding the hypothesis given below, the validity of the parallel slopes assumption is tested through comparing the value of $2(L_2 - L_1)$ with the table value of $X^2_{[K(J-2)]}$ in an attempt to indicate the likelihood value L_1 obtained from OLM and L_2 obtained from MLM (Long and Freese, 2006):

$$H_0 : \beta_{1k} = \beta_{2k} = ... = \beta_{(J-1)k} \; ; \; 1 \leq k \leq K \qquad (22)$$

Borooah (2002) stated that this test is not exactly a likelihood ratio test, however, it could be accepted as an indicator that the parallel slopes assumption is satisfied with a tremendous chi-square table value and a medium chi-square value will not guarantee that this assumption is provided.

COMPARISON OF MLM AND OLM OVER A REAL DATA ON INTEREST IN POLITICS

The data set used in this study was obtained from a study entitled ESS4-2008, ed.4.0, which was performed by the European Social Survey (ESS) during 2008-2009. The ESS is an academically-driven social survey designed to chart and explain the interaction between Europe's changing institutions and the attitudes, beliefs and behaviour patterns of its diverse populations. Within the scope of the survey study, a total of 56752 people were interviewed in 30 countries and information related with 662 variables were obtained. The data, which were obtained through the face-to-face meetings performed with totally 23475 people from Turkey and 10 countries that are the members of the European Union, were used in this study.

Table 2 displays the dependent and explanatory variables and their descriptive statistics within the scope of the study.

Table 2: Descriptive statistics

Variables	Frequency	Percent
Dependent variable :		
How interested in politics		
Very interested	2687	11.45
Quite interested	8635	36.78
Hardly interested	7187	30.62
Not at all interested	1966	21.15
Countries		
Belgium	1760	7.50
Germany	2751	11.72
Denmark	1610	6.86
Spain	2572	10.96
France	1073	8.83
United Kingdom	2351	10.01
Greece	2062	8.78
Ireland	1764	7.51
Netherlands	1778	7.57
Portugal	2361	10.06
Turkey	2393	10.19
Gender		
Male	10951	46.67
Female	12.514	53.33
Marital status		
Married	12584	10798
Not married	46.18	53.82
Ever had a paid job		
Yes	7957	69.88
No	3429	30.12
Age	47.56	18.48
Education		
Less than lower secondary education and other	5753	24.54
Lower secondary education completed	4392	18.74
Upper secondary education completed	6501	27.73
Post-secondary non-tertiary education completed	541	2.31
Tertiary education completed	6254	26.68

Examining the interest levels of participants in politics, it is observed that the rate of those who answered "Very interested" (11.45%) is almost the half of those who are "Not at all interested" (21.15%).

Examining the participants on the basis of countries, it is determined that the highest participation is from Spain (10.96%), while the lowest participation is from Denmark (6.86%). The survey study, which was participated by 2393 people from Turkey, was performed in cooperation with TUBITAK.

Examining the distributions of participants according to gender, it is observed that the distribution of females and males is almost equal. While a similar result is also valid for marital status, the rates of those who are married and who are not married are close to one another.

While a great majority of the survey participants (69.88%) has a wage-earning employment, it is observed that the rate of those who completed lower secondary education is very high (24.54%).

As it is already stated, the models that are used in accordance with the variable type utterly differ. Therefore, the scale type of the dependent variable shall be determined accurately.

Table 3: Multinomial logit model estimation results

Variables	Quite ınterested Coefficient RRRZ	($p > \|z\|$)	Hardly ınterested Coefficient RRRZ	($p > \|z\|$)	Not at all ınterested Coefficient RRRZ	($p > \|z\|$)
Constant	2.391	-	2.953	-	4.086	-
Age	-0.0120.988	-5.79(0.000)*	-0.0240.976	-11.23(0.000)*	-0.0240.976	-10.77(0.000)*
Gender						
Male	-0.5150.597	-7.43(0.000)*	-0.7620.467	-10.46(0.000)*	-0.9630.382	-12.41(0.000)*
Country						
Belgium	0.5531.738	3.02(0.003)*	1.3884.005	7.32(0.000)*	0.7242.063	3.77(0.000)*
Germany	-0.0540.948	-0.350.724	0.7902.204	4.92(0.000)*	-0.8820.414-	4.75(0.000)*
Denmark	0.0651.067	0.380.705	0.4941.640	2.63(0.008)*	-1.1920.304	-4.91(0.000)*
Spain	0.3211.379	1.620.106	1.7525.76	78.90(0.000)*	1.3763.958	7.07(0.000)*
France	-0.0420.959	0.270.786	-0.7022.018	4.30 (0.000)*	-0.4100.664	-2.39(0.017)*
United Kingdom	0.2521.288	1.590.111	0.6831.979	4.05(0.000)*	-0.2860.751	-1.64 0.101
Greece	0.1571.170	0.840.402	1.4724.359	7.88(0.000)*	0.8852.424	4.74(0.000)*
Ireland	0.1931.213	1.200.232	0.7722.164	4.52(0.000)*	-0.0190.981	-0.110.914
Netherlands	0.5111.667	2.88(0.004)*	0.6261.870	3.24(0.001)*	-0.1900.827	-0.940.347
Portugal	0.4021.495	2.24(0.025)*	1.3073.696	7.16(0.000)*	1.1503.158	6.45(0.000)*
Marital status						
Married	0.0171.017	0.230.816	-0.1040.901	-1.390.164	-0.3310.718	-4.19(0.000)*
Education						
Lower secondary education completed	-0.2000.818	-1.650.099	-0.6290.533	-5.12(0.000)*	-1.0890.337	-8.64(0.000)*
Upper secondary education completed	-0.5490.577	-4.86(0.000)*	-1.2070.299	-10.45(0.000)*	-1.8360.160	-15.17(0.000)*
Post-secondary non-tertiary education completed	-0.3880.679	-1.290.199	-1.4820.227	-4.59 0.000*	-2.9260.054	-6.78(0.000)*
Tertiary education completed	-1.0980.333	-10.03(0.000)*	-2.1910.112	-18.62(0.000)*	-3.0890.0	46- 22.68(0.000)*
Paid job						
Have job	0.0311.031	0.280.780	-0.0790.924	-0.720.475	-0.2970.743	-2.65(0.008)*
N = 11309	Log likelihood =-13363.536LR chi2(54) = 3067.60 Prob>chi2 = 0.0000*Pseudo R^2 = 0.1030					
Hausman-McFadden Test Chi2(37) = -7.29 (chi2<0)						

*: Coefficient is statistically significant at a significance level of 5%; RRR: Relative Risk Ratio; Base categories: Very interested, Female, Turkey, Not married, Less than lower secondary education and other, Have not job

Examining the dependent variable levels that show the interest *status* of individuals in politics, it is thought that it reflects a status, in other words, it is status based and there is a certain ordering between its levels. In that case, one of the methods to be recommended in modelling is OLM. On the other hand, whether the levels are indeed ordered or not could be revealed with the help of tests performed during the analysis phase. The fact that the interest of individuals in politics is also their own *choice* and that the data could be analysed with MLM, which is a choice-based model, is another approach that could be recommended in modelling.

During the rest of the study, the data will be modelled firstly by MLM and then by OLM with the help of the statistical package STATA 10. The validity of model assumptions will be tested and the remarkable results regarding the political interest levels of individuals living in ten countries that are the members of the European Union and Turkey will be presented over the accurate model.

Multinomial logit model results: Table 3 displays the MLM results. The validity of IIA assumption, which is the indicator of whether the accurate model is MLM or not, was initially researched with the help of Hausman-McFadden test.

Hausman-McFadden test: Examining Table 3, the test statistics value of Hausman-McFadden, which tests the hypothesis of:

H_0 : *Difference in coefficients is not systematic (IIA assumption is held)* was found to be -7.29.

In this case the chi-square is actually negative. We might interpret this as a strong evidence that we can reject the null hypothesis. This means that IIA assumption is not yielded here and we could not apply MLM to the data.

Ordered logit model results: Table 4 displays the OLM results. Parallel Slopes Assumption, which is the most important assumption of OLM, was initially tested here as in MLM. And then, as it is already stated, whether the dependent variable levels are ordered or not is revealed through the statistical significance controls of threshold parameters.

Table 4: Ordered logit model estimation results

Dependent variable: How interested in politics (1: very, 2: quite, 3: hardly, 4: not at all)	$\hat{b}$	SE	z	P>|z|	exp($\hat{b}$)
Age (A)	-0.0118	0.00100	-11.78	0.000*	0.988
Gender					
Male (M)	-0.4854	0.0365	-13.30	0.000*	0.615
Country					
Belgium (BE)	0.2392	0.0847	2.82	0.005*	1.270
Germany (GE)	-0.3334	0.08169	-4.08	0.000*	0.716
Denmark (DE)	-0.5057	0.09957	-5.08	0.000*	0.603
Spain (SP)	0.7748	0.075131	0.31	0.000*	2.170
France (FR)-	0.2346	0.08149	-2.88	0.004*	0.791
United Kingdom (UK)	-0.2998	0.08208	-3.65	0.000*	0.741
Greece (GR)	0.5381	0.08	056.69	0.000*	1.713
Ireland (IR)	-0.1082	0.08407	-1.29	0.198	0.897
Netherlands (NE)	-0.3382	0.0925	-3.66	0.000*	0.713
Portugal (PO)	0.6493	0.0742	8.75	0.000*	1.914
Marital status					
Married (MRD)	-0.2044	0.03691	-5.54	0.000*	0.815
Education					
Lower secondary education completed (LS)	-0.7339	0.05306	-13.83	0.000*	0.480
Upper secondary education completed (US)	-1.0614	0.05378	-19.73	0.000*	0.346
Post-secondary non-tertiary education completed (PS)	-1.5325	0.16203	-9.46	0.000*	0.216
Tertiary education completed (TE)	-1.7361	0.06084	-28.53	0.000*	0.176
Paid job					
Have job (HJ)	-0.2245	0.04725	-4.75	0.000*	0.799
Threshold parameters					
μ_1 = 0					
μ_2 = 2.01710			0.0334	0.000*	
μ_3 = 3.6598			0.0395	0.000*	
Parallel slopes assumption (Likelihood ratio test)					
chi2(36) = 359.76 (Prob>chi2 = 0.0000*)					
Model validity					
Log likelihood =-13543.418LR chi2(18) = 2707.84					
Prob>chi2 = 0.0000*Pseudo R^2 = 0.0909					

*: Coefficient is statistically significant at a significance level of 5%; Base categories: Female (FM), Turkey (TR), Not married (NMRD), Less than lower secondary education and other (L), Have not job

Test of the parallel slopes assumption and model validity : The validity of the Parallel Slopes assumption was researched with "Likelihood Ratio Test". Examining Table 4, the fact that the chi-square value (359.76) in the degrees of freedom of 36, which was obtained for the zero hypothesis test that was given with Eq. (22), is considered to be a great value indicates that the validity of the model assumption is highly probable, as explained by Borooah (2002) and this condition indicates that OLM might be a convenient approach for the modelling of the studied data. The LR statistics, which was estimated for the hypothesis of:

H . 0 The estimated model is insignificant

was found to be 2707.84. This statistics that shows a chi-square distribution with 18 degrees of freedom indicates that the model is significant at a significance level of 5%.

Test of the significance of the threshold parameters: There are two threshold parameters that will be estimated for a four-level dependent variable. As it is already stated, Greene (2000) suggested the normalization of the first threshold parameter to $\mu_1 = 0$. As is seen in Table 4, the second and third threshold parameters that are estimated are respectively $\mu_2 = 2.1710$ and $\mu_1 = 3.6598$ and they are significant at a significance level of 5%.

Test of the significance of the coefficients: Examining Table 4, it is observed that while $\hat{b}_{IR} = -0.1082$ (p = 0.198>0.05), which corresponds to Ireland (IR), is insignificant at a significance level of 5%; all other coefficients are statistically significant.

Thereby, the fact that the effects of explanatory variables are more significant on the dependent value compared to MLM is among the reasons why OLM is preferred to MLM.

Correct Classification Rate (CCR): As it is observed in the whole criteria above that measure the model quality, it is revealed that, OLM is a more accurate approach for modelling the data compared to MLM.

In the next section, the characteristics and significance degrees that affect the interest levels of individuals in politics were researched with OLM, which is determined to be the most convenient model for the data structure.

INTERPRETATION OF THE RESULTS OF THE TRUE MODEL OLM

Model: Taking the individual characteristics of i. into consideration, the equation is as follows,

$$\sum_{k=1}^{18} \hat{b}_k x_{ik} = \begin{pmatrix} -0.0118A & 0.4854M & +0.2392BE & -0.3334GE & -0.5057DE & +0.7748SP \\ -0.2346FR & 0.2998UK & +0.5381GR & -0.1082IR & -0.3382NE & +0.6493PO \\ -0.2044MRD & -0.7339LS & -1.0614US & -1.5325PS & -1.7361TE & -0.2245HJ \end{pmatrix} \quad (23)$$

and the probability estimations regarding the interest levels of the individual i. in politics are estimated with the following equations. (i = 1, 2, ..., 23475), (k = 1, 2, ..., 18):

$$P(Y_i = \text{"}very\ \text{int}erested\text{"}) = \frac{\exp\left(-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)} \quad (24)$$

$$P(Y_i \text{"}quite\ \text{int}erested\text{"}) = \left\{\frac{\exp\left(2.1710\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(2.1710\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}\right\} - \left\{\frac{\exp\left(\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}\right\} \quad (25)$$

$$P(Y_i \text{"}hardly\ \text{int}erested\text{"}) = \left\{\frac{\exp\left(3.6598\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(3.6598\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}\right\} - \left\{\frac{\exp\left(2.1710-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(2.1710-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}\right\} \quad (26)$$

$$P(Y_i = \text{"}not\ at\ all\ \text{int}erested\text{"}) = 1 - \left\{\frac{\exp\left(3.6598-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(3.6598-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}\right\} \quad (27)$$

Considering the Eq. (17), the probabilities regarding the interest level of the individual i. in politics as "very interested" or at a lower level; "quite interested" or at a lower level; "hardly interested" or at a lower level could be estimated with the equations respectively given below.

$$P(Y_i \le \text{"}very\ \text{int}erested\text{"};\ j=1) = P(y^* \le \mu_1 = 0) = \frac{\exp\left(-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)} \quad (28)$$

$$P(Y_i \le \text{"}quite\ \text{int}erested\text{"};\ j=2) = P(y^* \le \mu_2 = 2.1710) = \frac{\exp\left(2.1710-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(2.1710-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)} \quad (29)$$

$$P(Y_i \le \text{"}hardly\ \text{int}erested\text{"};\ j=3) = P(y^* \le \mu_3 = 3.6598) = \frac{\exp\left(3.6598-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)}{1+\exp\left(3.6598-\sum_{k=1}^{18} \hat{b}_k x_{ik}\right)} \quad (30)$$

Considering the fact that total cumulative probability is "1", the probability of the individual i. to be "not at all interested" or at a lower level will be "1" as well.
OLM results that are given in Table 4 could be interpreted under three titles given with Subsections 4.2, 4.3 and 4.4.

Interpretation of the estimated coefficients: While the increase in variables having significant and negative-signed coefficients indicates that the interest of individuals in politics will increase; the increase in variables having significant and positive-signed coefficients indicates that there will be a decrease in the interest of individuals in politics.

From this point of view, it is concluded that the interest of individuals living in Belgium, Spain, Greece and Portugal in politics is less than those who live in other countries. When they are compared with one another, it is revealed that those who live in Spain have approximately 3.24 times greater rates than those who live in Belgium regarding the interest in politics; 1.44 times greater than those who live in Greece and 1.19 times greater than those who live in Portugal.

In parallel with the increase in educational level, it is observed that the political interest levels of married male individuals having a job and live in Denmark, France, United Kingdom and Netherlands increase together with aging; the greatest increase is seen in the maternal age group who lives in Denmark and has an educational level of Tertiary.

Comparing the educational levels with one another, it is observed that regarding the interest levels in politics, individuals having an educational level of TE have approximately 1.13 times greater rates than those who

have PS; 1.64 times greater than those who have US; and 2.366 times greater than those who have LS.

Interpretation of the marginal effects on odds of the explanatory variables: $\exp(\hat{b}_M)$ values on the last column of Table 4 give the odds rates. Taking the basic categories into consideration, the interpretations of marginal effects upon the important variables are included in this section.

Gender:

Very Int.Quite Int. Hardly Int. Not at all Int.
Male (M) (-) effect on odds

Female (FM) (base): The odds rate for the male was found as $\exp(\hat{b}_M) = 0.615$. . Since this value is not greater than "1", the value 1.6260 is obtained when the reciprocal of this number is taken in an attempt to make the interpretation more comprehensible. However, it shall be remembered to replace the category of "Indicator" with the category of "Base".

Accordingly, the fact that the political interest levels of females compared to males are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 1.6260 times greater. In other words, it could be claimed that females are approximately 1.6260 times less interested in politics than males.

Country: Comparing the individuals living in countries that are the members of the European Union with individuals who live in Turkey, which is the only nonmember country among the countries that are included in the study, the points regarding whether their political viewpoints have changed and if so, to what extent they changed were revealed with the help of the following interpretations:

Very Int Quite Int. Hardly Int. Not at all Int.
Belgium (BE)
Spain (SP) (+) effect on odds
Greece (GR)
Portugal (PR)

Turkey (TR) (base): The odds rates obtained for BE, SP, GR and PR are respectively as 1.270, 2.170, 1.713 and 1.914. Accordingly, the fact that the political interest rates of individuals living in Belgium compared to the individuals living in Turkey are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 1.270 times greater; 1.270 times greater for Spain; 1.713 times greater for Greece; and 1.924 times greater for Portugal. Accordingly, compared to the individuals living in Turkey, the individuals living in these four countries that are the members of the European Union are apparently less interested in politics:

Very Int Quite Int. Hardly Int. Not at all Int.
Germany (GE)
Denmark (DE)
France (FR) (-) effect on odds
United Kingdom (UK)
Netherlands (NE)

Turkey (TR) (base): The odds rates estimated for GE, DE, FR, UK and NE are respectively as 0.716, 0.603, 0.791, 0.741 and 0.713. When the reciprocal of these values is taken, the values of respectively 1.397, 1.658, 1.264, 1.395 and 1.403 are obtained. Accordingly, the fact that the political interest rates of individuals living in Turkey are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 1.397 times greater than those who live in Germany; 1.658 times greater than those who live in Denmark; 1.264 times greater than those who live in France; 1.395 times greater than those who live in the United Kingdom; and 1.403 times greater than those who live in Netherlands.

To sum up, it is concluded that the status of being a member of the European Union may not be a determinant for viewpoints of individuals living in those countries regarding some very important subjects such as politics.

Marital status:

Very Int Quite Int. Hardly Int. Not at all Int.
Married (MRD) (-) effect on odds

Not married (NMRD) (base): The odds rate for MRD was found as 0.815. When the reciprocal of these values is taken, the value of 1.225 is obtained. Accordingly, the fact that the political interest rates of married individuals compared to not married individuals are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 1.225 times greater. Accordingly, it is understood that married individuals are more interested in politics:

Education:

Very IntQuite Int.Hardly Int.Not at all Int.
LS
US(-) effect on odds
PS
TE

Less than LS and other (base): The odds rates for LS, US, PS and TE are found respectively as 0.480, 0.346, 0.216 and 0.176. When the reciprocal of these values is taken, the values of respectively 2.083, 2.890, 4.629 and 5.682 are obtained. Accordingly, the fact that the political interest rates of individuals having an educational degree of "Less Than LS and Other" are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 2.083 times greater than that of individuals having LS degree; 2.890 times greater than

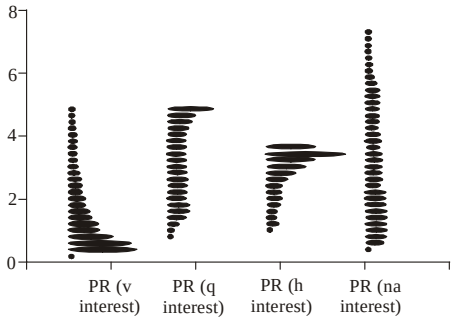

Fig. 1: The graphical representation of the estimated probabilities

that of individuals having US degree; 4.629 times greater than that of individuals having PS degree and 5.682 times greater than that of individuals having PS degree. Examining the results carefully, important increases were also determined on the political interest rates of individuals together with the increasing educational level.

Paid job:

Very Int. Quite Int. Hardly Int. Not at all Int.
Have Job (HJ) (-) effect on odds

Have not job (base): The odds rate for HJ was found as 0.799. When the reciprocal of these values is taken, the value of 1.252 is obtained. Accordingly, the fact that the political interest rates of individuals who have no job compared to those who have a job are "not at all" when compared with "hardly" or a higher level indicates that the odds is approximately 1.252 times greater. Accordingly, it could be claimed that having a job causes the increase of the interest rate in politics, as well.

Interpretation of the estimated probabilities: Using the functions given with Eq. (24)-(27), probability estimations of four different political interest levels were performed for each individual and the results were diagramed as follows.

Examining Fig. 1, the predicted probabilities for the "very interested" tend to be less than 0.20, with the majority of predictions for the middle categories falling between 0.20 and 0.40. In only a few cases, the probability of any outcome is greater than 5.

CONCLUSION

Today, the most frequently referenced questioning technique for the determination of the behavioral preferences of individuals is consisted of questions, which has scale-based variable types. However, this variable occasionally determines the behavioral preference and also puts these preferences in an order, due to its structure. In this case, the variable becomes an ordered variable. The analysis and assessment of the behavioral status expressed by such variables will only be possible through the use of the accurate method.

There is a great variety of analysis methods that could be used depending on the structure of the dependent variable. As it is explained, the variable not only expresses a choice status, but also becomes two approaches called Multinomial Logit Model (MLM) and Ordered Logit Model (OLM) that could be used in these circumstances, if it is ordered. However, both of the methods shall necessarily include assumptions and in addition to this, the status of "being ordered" regarding the variable shall be statistically tested.

In this study, the theories and assumptions of the aforementioned two approaches were discussed in detail. And then the political interests of individuals, who express a "status" and also possess an "ordered" structure, were modelled with both of the approaches and the assumptions were tested.

As a result of the analyses performed with the MLM, it was observed that IIA assumption, which is the most important assumption of the model, was not provided. Thereby, it will be a mistake to approach the status of being interested in politics as a preference; and model and interpret it with the multinomial model.

Following the MLM, the OLM which approaches the status of being interested in politics in an ordered way was applied. Regarding the OLM, it was observed that parallel slopes assumption and model validity assumptions were provided separately. As well as these two assumptions, there is another important assumption in this approach: statistical significance of threshold parameters. Unless this assumption is provided, it will be deceptive to approach the dependent variable as an ordered variable and model it in this direction. According to the results obtained with the OLM, both of the threshold parameters were found statistically significant. Thus, the OLM was concluded to be an accurate approach for the modelling of the dependent variable. In this study, which researched the interest levels of individuals in politics, the results of the OLM were summarized as follows.

As a result of this study, which examined the political interest level via 11 countries and modelled it with OLM, it is observed that women are less interested in politics than men. Today, where women-men inequality, in other words gender apartheid can not be removed even in developed countries, this approach of women against the political arena, which is the authority that will provide their own social rights, shows that the aforesaid problems will not be solved in the near future.

The fact that married individuals are more interested in politics than those who are not is an expected situation. However, including the young population within politics

is important in terms of generating new viewpoints and consequently alternative solutions for political problems.

Another result that is obtained from the OLM is that the individuals who have a job are more interested in politics than those who do not. This condition indicates that politics is still being conducted by people above a certain income level in the whole society and that it has not been spreaded throughout the base in spite of all efforts. The result of another model that supports this determination is that the political interest level increases in parallel with the increase of the educational level. While individuals with a high educational level constitute a small section of society especially in developing countries, this section also conducts the politics that affect the whole society.

Examining the interest of Turkey and societies of countries that are the members of the European Union in politics, it was observed that individuals living in Greece, Portugal and Spain are less interested in politics than those who live in Turkey. As from the period of the implementation of the survey, economic crisis started in those countries. The fact that the economic crisis could not be kept under control by politicians sufficiently decreased the faith in politicians in these three countries in the eyes of the society and consequently, the interest in politics decreased as well. It was observed that the political interest of people living in Belgium is less than those living in Turkey. The reason of this condition is that unlike Greece, Portugal and Spain, this country is among the first ten countries having the highest level of welfare. Even though it is an unnatural-structured country, the Belgium society does not have a political-based problem since they are highly pleased with the level of welfare. Thereby, they are less interested in political affairs compared to Turkey.

As a result of the OLM, it was observed that the people living in countries such as Germany, Denmark, France, United Kingdom and Netherlands are more interested in politics than those living in Turkey. Examining the general structure of these countries, it is seen that they have a higher level of welfare and also they comprise the locomotive countries of the European Union. Even though the people living in these countries do not have economic problems, it is revealed that societies are sensitive in respect of especially the aids to be made for crisis countries and the future of the Euro region and consequently, they are more interested in politics.

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