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An Empirical Analysis of Television Commercial Ratings in Alternative Competitive Environments Using Multinomial Logit Model

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Abstract

Watching the commercials depends on the choice of the viewer. Most of the television viewing takes place during "Prime-Time" unfortunately; many viewers opt to zap to other channels when commercials start. The television viewers' demographic characteristics may indicate the likelihood of the zapping frequency. Analysis made by using Multinomial Logit Model indicates how effective the demographic variables are in the watching rate of the first minute of the television commercials.

***Keywords**: Television, Commercial, Prime-Time, Multinomial Logit Model*

***JEL Code Classification:** C44, G21, L25*

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1. Introduction

Watching commercials shown during television programs is totally the choice of the viewer. The effectiveness of the commercials is in direct proportion to the watching rate of the television programs. When television programs are being watched the most, called "Prime-Time", in the nights during television advertisements among television programs is thought as a time period to travel other channels. In this research the demographic characteristics of the viewers are analyzed especially in the first minute viewers to determine differences among the channels.

In literature similar studies include: Darmon's (1976) research on the factors of watching television which used regression analysis to compare the behavior of the viewers. Rust and Eechambadi (1989) developed a way to analyze the flow of viewers according to the program type. Tavakoli and Cave (1996) reduced the time period and researched the categorical variables by using the Logit Model, viewers were analyzed for their appreciation and channel and program varieties. Alwitt and Prabhaker (1994) researched the causes of avoiding commercials according to income level, attitudes toward television and age variables. Lui et al (2004) pointed out the commercial broadcasting industry consists of two distinct but closely related markets one for the viewers and the other for advertisers. Advertisers are likely to achieve a target number of gross ratings points over the duration of the commercials (Givon & Grosfeld-Nir, 2008; Kelton & Schneider Stone, 2008). Barwise and Ehrenberg (1988), Vogel (1998), Dukes and Gal-Or (2003) researched that advertisers spent more time for air time in programs with more viewers than in programs with fewer viewers. Siddarth and Chattopadhyay (1998) thought of the subject of zapping channels as a probability model and looked at two different categories which were whether the viewer stayed on the channel or not. While doing this they tested the time the viewers have stayed at the channel. The research has proven that there was no difference between remaining at the channel for 15 seconds and 30 seconds. Patzer (1991), Singh and Cole (1993), Newell and Henderson (1998) have done several researches to prove that 30 seconds of air time is better for the viewer to recognize the product compared to 15 seconds. Therefore, as described in this research, one minute of commercial is more than enough to serve its purpose. Song (2005) mentions a lot of factors for avoiding commercials on television.

The research includes the following parts: In the second part Multinomial Logit Model is introduced. Third part presents implementation and the data set including the research methodology and variables with descriptive statistics. There are also models to predict the results. The last offers conclusions and recommendations in future studies.

2. Multinomial LOGIT Model

Multinomial Logit Model (MNLM) is extended Logit Model that contains more than two dependent outcome variables. MNLM is not a linear model but converges to the linearity by using parameters logit transformations in Generalized Linear Model. (McCullagh and Nelder, 1989). To formulate MLNM, let there are k explanatory variables and an intercept term denoted b $X_i=(x_{0i}, x_{1i},\ldots, x_{ki})$ vector of length (k+1) where $x_{0i}=1$ in the analysis involving independent subjects. The conditional probability of m^{th} level of response variable which depends on explanatory variables is shown by;

$$\pi_{im} = P(Y=m|x) = \frac{e^{\beta_i X_i}}{\sum_{t=1}^{M} e^{\beta_i X_i}} \text{; m=1,2,…,M; i=1,2,…,n} \tag{1}$$

where $\beta_i = (\beta_{m0}, \beta_{m1}, \ldots, \beta_{mk})$ is a vector of unknown parameters.

Multi-categorical MNLM works same as binary logit model that compares logit pair orderly and find distinct interpretations and effectiveness of prediction of parameters. Binary logits yielding the result of a reference category is determined by making comparisons. (Hosmer and Lemeshow, 2000). Thus the logit for the mth such comparison with respect to referent level is given by;

$$g_L = ln\left[\frac{\pi_{im}}{\pi_{iM}}\right] = \beta_{m0} + \beta_{m1}X_{m1i} + \beta_{m2}X_{m2i} + \cdots + \beta_{mk}X_{mki}\text{;m=1,2,…,M-1} \tag{2}$$

In terms of logit function and using condition $g_L = 0$ the general expression for the conditional probability given in (1) can be written as:

$$P(Y=m|x) = \frac{e^{g_m}}{1+\sum_{t=1}^{M-1} e^{g_t}} \text{; m =1, 2,… , M-1} \tag{3}$$

The MNLM explanatory variables' effects are shown in terms of log-odds by using maximum likelihood. Putting in order the (L-1) is more practical and effective than using binary logits. In this way, all the sets of data likelihood is controlled.

2.1. Maximum Likelihood

In MLNM, it is defined the estimation of vector parameters methods. There are L-1 binary logits $(\mathrm{Y}_1, \mathrm{Y}_2, \mathrm{Y}_3, \ldots, \mathrm{Y}_{(L-1)})$.The effects of explanatory variables are shown in terms of log-odds ratios by using Maximum Likelihood Estimation (ML). Instead of binary logits, this time (L-1) logits is used which is more effective and practical. In this way all the likelihood of all data set can be controlled at once. Likelihood function is thought as lst category in Y and ith person's answer. In this case for i th person, it is arranged as, $Y_{i1} = 0, Y_{i2} = 0, \ldots, Y_{il} = 1, Y_{iL} = 0$.

The probability is denoted as:

$$\tau_{il} = P(Y_{il} = 1) = (\tau_{i1})^0 (\tau_{i2})^0 \ldots (\tau_{il})^1 \ldots (\tau_{iL})^0 = \prod_{l=1}^{L} (\tau_{il})^{Y_{il}} \tag{4}$$

Then, likelihood function for n independent observation and Y dependant variable with L categories is;

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

It is known that $\sum_{l=1}^{L} Y_{il} = 1$ and likelihood function's natural logarithm is taken for every person i, the likelihood function is;

$$\ln(\varphi) = \sum_{i=1}^{n}\left[\sum_{l=1}^{L-1} Y_{il}\Psi_l - \ln\left\{1 + \sum_{l=1}^{L-1} e^{\Psi_l}\right\}\right] \tag{6}$$

The likelihood equations are found by taking first derivative of $\ln(\varphi)$. $\ln(\varphi)$ includes (L-1) x (k+1) unknown parameters. So, the estimated maximum likelihood values are differentiated from (6) and shown as $\widehat{Y}_1, \widehat{Y}_2, \widehat{Y}_3, \dots, \widehat{Y}_{(L-1)}$ for finding vectoral parameters' likelihood equations are equaled to zero. Parameters are in non-linear types; their solutions are found by Newton-Raphson method. Iterative procedures are used to find out estimations. At the end ML is referred as (-2LL), negative two likelihood. (Train, 2009)

2.2. Model Fit

For overall fit of the model instead of R^2 in linear regression Deviance and Pearson statistics are used in logistic regression models. With ML, different iterations are used to find the best solution which is the smallest possible deviance or best fit.

Pearson:

$$X^2 = r(y_j, \hat{\pi}_j) = \frac{(y_j - m_j\hat{\pi}_j)}{\sqrt{m_j\hat{\pi}_j(1-\hat{\pi}_j)}} \rightarrow X^2 = \sum_{j=1}^{J} r\left(m_j\hat{\pi}_j\right)^2 \tag{7}$$

Deviance :

$$d(y_j, \hat{\pi}_j) = \pm\left\{2\left[y_j \ln\left(\frac{y_j}{m_j\hat{\pi}_j}\right) + (m_j - y_j)\ln\left(\frac{m_j - y_j}{m_j(1-\hat{\pi}_j)}\right)\right]\right\}^{1/2} \tag{8}$$

$(y_j - m_j\hat{\pi}_j)$'s sign is given same as (+) and (-) signs in formula m_j where j gives the total value belongs to the category. Accordingly:

$$D = \sum_{j=1}^{J} d\left(y_j, \hat{\pi}_j\right)^2 \tag{9}$$

is found in this way. (Hosmer and Lemeshov, 2000).

Both statistics measure the Goodness of Fit with (number of parameters in saturated model - the number of parameters in estimated model) degrees of freedom and X^2 distribution. Deviance statistic is called -2LL by Cohen at al. (2003) and D by Hosmer and Lemeshov and it can be thought of as a chi-square value.

2.3. The Likelihood Ratio Test

The statistic is usually used that compares the fit of the model with and without predictors. It tests the significance of coefficients in the model.

$$D = -2\ln\left[\frac{Maximum\ Likelihood\ of\ the\ Restricted\ Model}{Maximum\ Likelihood\ of\ the\ Non\text{-}restricted\ Model}\right] \tag{10}$$

Restricted model refers to a logistic model which has constant –only model and non-restricted model refers to a logistic model that includes all desired effects or k-number of predictors. The difference between these two deviance values is referred as G for goodness of fit and likelihood ratio test.

$$G = X^2 = D(for\ the\ model\ without\ the\ variable) - D(for\ the\ model\ with\ the\ variable)$$

$$G = X^2 = -2\ln\left(\frac{L_{null}}{L_k}\right), \tag{11}$$

where the ratio of ML values are found by taking the log and multiplying by -2.
If J is the number of categories dependent variable and I is the number of estimated parameters, then this statistic has X^2 distribution with ((J-1). (I-1)) degrees of freedom (Agresti, 2002). The hypotheses for the coefficients are given below:

$$\text{Ho: } \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \beta_p \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \text{ and H1: } \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \beta_p \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \tag{12}$$

2.4. Wald Test

Wald statistic is used to show whether estimated regression coefficients for the mentioned predictors are significantly different from zero. If the coefficient is significantly different from zero, then it is assumed that the predictor is making a significant contribution to the prediction of outcome.

$$\text{Wald}= \left[\frac{\hat{B}_j}{SE(\hat{B}_j)}\right]^2 \tag{13}$$

where $\hat{B}_j$: is the estimated regression coefficient and $SE(\hat{B}_j)$ represents the standard error of estimated coefficients.
Estimated regression coefficients and their standard errors are used to compute a t-statistic. Wald statistic is basically identical to the t statistic in linear regression and has X^2 distribution with 1 degree of freedom. (Azer and Walker, 2011)

2.5. Pseudo R^2

This statistic has similar meaning as R2 in linear regression. It can vary between 0 and 1. Zero means predictors are useless at predicting the outcome variable and one means that the model predicts the outcome variable perfectly. There are different R2 in logistic regression and conceptually they are somewhat the same.

Cox and Snell's R2 (1989) which is based on the log likelihood of the model (LL (new)) and the log likelihood of the original model (LL (baseline)), and sample size, n;

$$R_{cs}^2 = 1 - e^{\left[-\frac{2}{n}LL(new)-LL(baseline)\right]} \tag{14}$$

Another type of R^2 is Nagelkerke's R^2 (1989) which also uses the R_{cs} in computation;

$$R_N^2 = \frac{R_{CS}^2}{1-e^{\left[\frac{2LL(baseline)}{n}\right]}} \tag{15}$$

There are several measures intended to mimic the R^2 analysis in logistic regression; but none of them as the R^2 in linear regression. The interpretation is not the same, but they can be interpreted as an approximate variance in the outcome accounted by the independent variables. (Hosmer and Lemeshov, 2000)

The assumption of Multinomial Logit model is a principle of Independence Irrelevant of Alternatives (IIA). Property of independence among the alternatives

implies that two alternatives to the rate of probabilities to be independent of the available alternatives is defined as being independent from the third alternative. Deviations from the independence assumption change the MNLM. Differential rates are not affected by the existence of alternatives to choose regardless of the presence of a third alternative. Hausman test is applied on behalf of the dependent variables to see the independence of Alternatives removing one of the restricted model compares with the unrestricted model forecasts. If a significant difference is observed between these two models, this assumption is not valid.
Hausman test statistic is as follows:

$$X^2 = \left(\hat{\beta}_s - \hat{\beta}_f\right)' \left[\hat{V}_s - \hat{V}_f\right]^{-1} \left(\hat{\beta}_s - \hat{\beta}_f\right)$$

Here, s is a restricted model; f is the set of unrestricted choice of the model; $\hat{V}_s$ and $\hat{V}_f$ are, respectively, based on estimates of the asymptotic covariance matrix. (Hausman and McFadden,1984)

3. Materials and Methods

In this research, four national television channels in Turkey are analyzed with respect to the watch rate of commercials in the first minute, during hours between 20.00-00.30 and from March 2010 until April 2011. During this time period, data is gathered from the Rating Company accepted by TUIK (Türkiye İstatistik Kurumu). The four national television channels that follow the same policy in broadcasting will be called Channel1, Channel2, Channel3, and Channel4. Hence, the Channel dependent outcome variable has four nominal categories. 51,800 people were surveyed electronically and MNLM was used as the analysis method. By using random sampling method One year's data are selected and MNLM method specification is controlled in accordance with the Hausman test. It has been proposed that differences in demographic structure including gender, age ranges, and socio-economic status, influence viewers' choice of channel.

Stata 11.1 software program is used to find out test results.

3.1. Variable Definitions

Channel: Channel is a dependent variable, in nominal scale and consisting of four categories: Channel1, Channel2, Channel3, and Cahnnel4. Viewership of the four different channels is distributed as follows; 12,051 respondents from Channel1, 13,420 respondents from Channel2, 12,946 respondents from Channel3, 13,383 respondents from Channel4.

Gender: Gender is an independent variable, in nominal scale consisting of two categories: Male and Female. 0 for women, and 1 for men were used for the encoding of 29,455 female and 20,345 male respondents.

Age: Age is also an independent variable that is in ordinal scale consisting of five categories generated as follows: 5-11 years (1), 12-19 years of age group (2), 20-34 years (3), 35-44 years (4), and 45 and above (5). Thus, all ages starting from 5 are included in the research. Number of respondents in each age group is as follows; 4,018 respondents in (5-11) age group, 6,506 respondents in (12-19) age group, 12,872 respondents in (20-34) age group, 10,053 respondents in (35-44) age group, 18,351 respondents in (45 and sbove) age group.

Socio-economic status: Socio-economic status is an ordinal scale. Even though in the determination of socio-economic status of individuals or households, not only income but also other indicators such as educational level, place of residence, occupation, and ownership of certain products are typically used, in this study, households in Turkey are divided into four segments based only on income reported in TUIK data (TUIK, 2009). These segments are designated as A, B, C, and D, ranging from highest to the lowest. Number of respondents in each group is, respectively, 11,511; 16,026; 19,613; 4,650.

3.2. Descriptive Statistics

Descriptive statistics obtained from 51,800 individuals are presented in Table 1.

Table 1: Descriptive Statistics

Variables	Mean	Observations	Percent of Observations	Standard Deviation	Minimum	Maximum
Channel	**2.5339**	**51,800**	**100**	**11,094**	**1**	**4**
Channel1	0.2326	12,051	23.26	0.4225	1	1
Channel2	0.2590	13,420	25.91	0.4381	2	2
Channel3	0.2499	12,946	24.99	0.4329	3	3
Channel4	0.2583	13,383	25.84	0.4377	4	4
Gender	**0.4313**	**51,800**	**100**	**0.4952**	**0**	**1**
Female	0.5686	29,455	56.86	0.4952	0	0
Male	0.4313	20,345	43.14	0.4952	1	1
Age	**3.6218**	**51,800**	**100**	**12,885**	**1**	**5**
5-11	0.0775	4,018	7.76	0.2674	1	1
12-19	0.1255	6,506	12.56	0.3313	2	2
20-34	0.2484	12,872	24.85	0.4321	3	3
35-44	0.1940	10,053	19.41	0.3954	4	4
45 – older	0.3542	18,351	35.43	0.4782	5	5
Socio-	**2.3359**	**51,800**	**100**	**0.9203**	**1**	**4**
economic Status	0.0897	11,511	22.22	0.2888	4	4
A	0.3786	16,026	30.94	0.4850	3	3
B	0.3093	19,613	37.86	0.4622	2	2
C	0.2222	4,650	8.98	0.4147	1	1
D						

Of the people that watched television advertisements in the first minute 56.86% were females and 43.14% were males. (5-11) age group included 7.76% of the sample while (12-19) age group included 12.56%. (20-34) age group and (35-44) age group each comprised almost a quarter of the audience (24.85% and 19.41%

respectively). (45 and older) age group included 35.43% of all viewers. Socio-economic levels of the first minute advertising viewers were as follow: Status A has a rate of 22.22%, status B has a rate of 30.94% and status C has 37.86%. Status D has the lowest rate of 8.98%.

3.3. Research

The purpose of the research is to ascertain specific features of the interrelationship between audiences' characteristics and to compare television channels during the first minute of commercials. One used independent variables such as gender, age, and socio-economic status (ses) to compare viewership ratings during first minute of television commercials in each television channels by using multinomial logit model. The study enlisted the help of 51,800 television viewers. Research objective was to determine whether or not viewers select a given television channel during the first minute of commercials and to ascertain if such selecting is influenced by gender, age group ,and socio-economic status.

The fit between the object model and the model estimated with knowledge of primarily used data was measured. This is illustrated in Table 2, including the significance of each independent variable.

Table 2: Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2637,733			
Final	1936,836	700,897	9	,000

The goodness of fit is statistically significant, and Pearson and Deviance values are reasonable in Table 3.

Table 3: Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1127,018	105	,000
Deviance	1139,330	105	,000

Apart from this, the Pseudo R2 values have come out low in Table 4. This situation is caused by the structure of the variables and shows different pseudo R^2 values for closeness and fit.

Table 4: Pseudo R-Square

Cox and Snell	,013
Nagelkerke	,014
McFadden	,005

As noted earlier, the significance of independent variables in logistic regression, and the output LR test is measured by the effects of each separately. Table 5 indicates that all of the independent variables contributed significantly to the outcome.

The hypothesis that all the coefficients associated with respectively gender, yas, and ses are simultaneously equal to zero –can be rejected at the 0.01 level. (all X^2, df and p values are given in Table 5.)

Table 5: Likelihood-ratio Tests for Independent Variables

Channel	**Chi^2**	**Df**	**p>Chi^2**
Gender	77.546	3	0.000
Age	81.950	3	0.000
Socio-econ. Status	542.207	3	0.000

Ho: All coefficients associated with given variable(s) are 0.

Another way is to estimate the full model including all of the variables, resulting in Wald test statistic in Table 6. According to the Wald test results; the effect of gender on Channels is significant at the 0.01 level (X^2=77.53, df=3, p=0.00).The effect of age on Channels is significant at the 0.01 level (X^2=81.79, df=3, p=0.00).The effect of ses on Channels is significant at the 0.01 level (X^2=535.26, df=3, p=0.00). Overall, it is said that all the independent variables contributed significantly to the model.

Table 6: Wald Tests for Independent Variables

Channel	**Chi^2**	**Df**	**p>Chi^2**
Gender	77.534	3	0.000
Age	81.792	3	0.000
Socio-econ. Status	535.257	3	0.000

Ho: All coefficients associated with given variable(s) are 0.

The coefficient estimates of model parameters are analyzed for overall statistics (Coefficient), Wald statistics (RRR) and odds related significance levels (p), are shown in Table 7.

Table 7: Model Parametric

	Category	Channel1			Channel2			Channel3		
		Coefficient	RRR	p	Coefficient	RRR	p	Coefficient	RRR	p
Constant		0.053		0.351			0.000	0.563		0.000
Gender[1]	Male	-0.065	0.937	0.010	-0.205	0.814	0.000	-0.195	0.823	0.266
Age[2]	(12-19)	-0.493	0.611	0.000	-0.444	0.641	0.000	-0.065	0.937	0.000
	(20-34)	-0.298	0.742	0.000	-0.640	0.527	0.000	-0.463	0.629	0.000
	(35-44)	-0.321	0.726	0.000	-0.641	0.527	0.000	-0.382	0.682	0.000
	(45 +)	-0.267	0.766	0.000	-0.494	0.610	0.000	-0.322	0.725	0.000
Socio-economic Status[3]	B	0.185	0.044	0.000	0.241	1.273	0.000	-0.021	0.979	0.521
	C	0.199	0.042	0.000	0.164	1.178	0.000	-0.390	0.677	0.000
	D	0.312	0.065	0.000	-0.106	0.899	0.031	-0.650	0.522	0.000

Channel 4 using multiple logit model in Table 7 are examined with reference to the expected signs of the coefficients in the expected direction and were statistically significant. Odds ratios according to variables using the comments made in the first minute advertisement tracking reveals the preferences of the channel.

The gender of the person viewing the advertisement in the first minute of the advertisement broadcast could be predicted significantly. The change in odds ratio (RRR) while gender changes from female to male, gives the viewers' rate ranking. Channel decision of males with respect to females is in a descending order: Channel4, Channel1, Channel3, and Channel2. The channel decision of female viewers is just the opposite of male viewers'; Channel2, Channel3, Channel1, Channel4.

The age group of the person being watched the advertisement in first minute whenever they broadcast on television channels predicted significantly. At the age variable, (5-11) age group is chosen as the reference category. According to this reference group; (12-19) age group viewers are more likely to watch Channel4. After Channel4, the channels come up with in descending order: Channel3, Channel2, and Channel1. Besides the choice rate of Channel4 and Channel3 are very close to each other and so Channel2 and Channel1 are, the selection rate of Channel4 is twice times more than the selection rate of Channel1.

According to (5-11) age reference group; (20-34) age group viewers are more likely to watch Channel4. After Channel4, the channels come up with in descending order: Channel1, Channel3, and Channel2. In this age group, the viewers' selection of Channel4 is twice times more than the viewers' selection of Channel2 and the viewers' selection of Channel2 is quarter times more than the viewers' selection of Channel3.

(35-44) age group audiences' channel decisions according to (5-11) age reference group are the same as an order of (20-34) age group decisions: Channel 4, Channel1, Channel 3, and Channel2. Although the channel watching order is the same, odds ratios are different from the previous age group.

(45 and older) audiences with respect to (5-11) age group, have same tendency choosing channels with the age groups (20-34) and (35-44): Channel4, Channel1, Channel3, Channel2. Although it is seen same order in channels with the different age groups, odds ratios are different the age groups. Thus, with increasing age from the age of 20 viewers prefer to watching first minute advertisement trends in the channels does not change even if watching rates change.

Whether the socio-economic status was different significantly predicted whether the channels are different or not. Table 5 shows that the channel preferences change according to changing of socio-economic status. Socio-economic levels affect the audience's channel choice. At the socio-economic status variable, a socio-economic status group is chosen as the reference category. According to this reference group; B socio-economic status group viewers are more likely to watch

Channel2. After Channel2, the channels come up with in descending order: Channel1, Channel4, and Channel3. All channels preferred rates are close to each other even though cross-channel views of at least 20% of CH2 is preferred more than others.

C socio-economic status group viewers' with respect to A socio-economic status group viewers' make decision among channels and in first minute television advertisement this status group viewers chosen the most preferred to least as follow: Channel1, Channel2, Channel 4, Channel 3. Channel1 is chosen two times more than Channel3 while not so much differences between Channel1 and Channel2.

D socio-economic status group viewers' with respect to A socio-economic status group viewers' make decision among channels and in first minute television advertisement this status group viewers chosen the most preferred to least as follow: Channel1, Channel4, Channel2, and Channel 3. In this status the second and third places are changed when it is compared with the status C. In D status, Channel 3 viewers have at least watched channel this status and was preferred by half of the channel to Channel1.

In all status group viewers, in generally, the most preferred channels might change but all the time the least preferred one is the Channel3.

Independence of Irrelevant alternatives, IIA should be used for the first minute of the viewers channel choice. IIA's validity is determined by Hausman Test developed by Mc Fadden and Hausman. Table 8, Hausman test results are analyzed IIA's can be seen that it is not rejected. MNL model type for this model can be applied in this case is the analysis applies to the outputs.

Table 8: Hausman tests of IIA assumption

Omitted	Chi^2	Df	$p>Chi^2$	Evidence
Channel 1	-471.55	4	1.000	for Ho
Channel 2	-396.043	4	1.000	for Ho
Channel 3	-464.449	4	1.000	for Ho
Channel 4	-487.134	4	1.000	for Ho

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

4. Results and Discussion

In this study, the first minute of advertising was analyzed using MNLM in four National Turkish Channels and monitored to see if whether there are differences between the viewership rates of the channels. Model results revealed that each independent variable used in the model have different effects on television advertisement tracking.

All factors are effective in influencing channel choice for first minute advertisements. Gender seems to influence viewership of channel first minute ads.

Most of the female audiences choose Channel2 while most of male prefer Channel4. It must be admitted, however, that differences for genders appear to be quite small.

Age is another factor for choosing a channel for first minute ads. It is stated that for all age categories, Channel4 has the highest viewership. It may be surmised that the data can be viewed as two distinct age groups: 20 and under, 20 and over. Because there is an order of first minute ads ratings for ages below 20 and there is another order of first minute ads ratings for ages above 20. Therefore, advertisers think of ages as two groups when they promote their products in accordance with preferred channels.

Socio-economic status affects the viewership ratings during first minute of television commercials. When socio-economic status increases, the rate of viewing advertisement in Channel2 also increases. This situation is just the opposite for Channel1. While D status audiences choose the Channel2 at the third place, C status audiences choose it at the second place and B status audiences choose it at the first place. In all status audience, Channel3 have the lowest rating level. Channel3 is the least attractive channel for any status of first minute of television commercials audiences.

Advertisers regard information on the profiles of viewers of commercials and their channel choices as desirable inputs. This study enables predictions of viewers' choices on the basis o certain characteristics. Considering the high cost rates of first minute commercials on television, advertisers and advertising agencies who want to promote their products, should prefer the most effective channel. Moreover, in order to reach targeted segments of population, they should determine the matching channels.

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