A Model for Tourism: The Total Number of Trips by Main Mode of Transport Used in 13 EU Countries

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Abstract: *In this study, we consider and estimate the most accurate association model of the Categorical Data Analysis (CDAS) for tourism: the total number of trips (absolute value/unit) by main mode of transport used in 13 EU countries. The data used in this study were obtained from the Eurostat and were estimated on actual base year from 2000 - 2008. Since the main focus is to have a better understanding of tourism - holidays in 13 EU countries, the analysis of association (ANOAS) table is given in order to ascertain the percentage of the data which is covered by each model. We find and estimate the association model with the best fit and in conclusion we find out that the row-column effect model RC (M = 8) has the best fit among all.*
Keywords: *Association models, Log-linear and non-linear models, European Union and tourism*

1. INTRODUCTION

The statistical definition of tourism is broader than the common everyday definition. It comprises not only private trips but also business trips. This is primarily because it views tourism from an economic perspective. Private visitors and business visitors have broadly similar consumption patterns. They both make significant demands on transport, accommodation and restaurant services. To providers of these services, it is of secondary interest whether their customers are private tourists or on business. Tourism promotion departments are keen to combine both aspects by emphasizing the attractiveness of conference locations as tourist destinations in their own right and feature these services in marketing activities.

Tourism is an important and fast-evolving economic activity with social, cultural and environmental implications, involving large numbers of small and medium-sized businesses. Its contribution to growth and employment varies widely from one region of the EU to another. In rural regions that are usually remote from the economic centers of their countries, tourism is often one of the main sources of income for the population and a prominent factor in securing an adequate level of employment.

The crucial role that tourism plays in generating growth and jobs, its growing importance and its impact on other policy areas ranging from regional policy, diversification of rural economies, maritime policy, employment, sustainability and competitiveness to social policy and inclusion ('tourism for all') are widely acknowledged all over the European Union. Therefore, tourism is reflected in EU policy as well as in national policies. The Lisbon Treaty acknowledges the importance of tourism, outlining a specific competence for the European Union in this field.

The statistically important factor is the usual place of residence of the visitors, not their nationality. Foreign visitors, particularly from far-away countries, usually spend more per day than visitors from the same country during their trips and thus generate greater demand for the local economy. Their expenditure also contributes to the balance of payments of the country visited. They therefore help to offset foreign trade deficits.

According to the UN World Tourism Organization, Europe is the most frequently visited region in the world. In 2009, five of the top 10 countries for visitors in the world were European Union Member States. The wealth of its cultures, the variety of its landscapes and the exceptional quality of its tourist infrastructure are likely to be part of the explanation. Enlargement hugely enriched the EU's tourism potential by enhancing cultural diversity and providing interesting new destinations to discover.

An analysis of the structure of and trends in tourism in Europe's regions confirms the compensatory role which this sector of the economy plays in many countries. It is particularly significant in regions remote from the economic centers of their country. There tourism services are often a prominent factor in securing employment and are one of the main sources of income for the population. This applies especially to Europe's island states and regions, to many coastal regions, particularly in southern Europe, and to the whole of the Alpine region. The particularly dynamic growth in tourism in most of the 'new' central and eastern European Member States is a significant factor in helping their economies to catch up more rapidly with those of the 'old' Member States.

A report conducted by the World Tourism Organisation (WTO), during the Global Tourism Forum 2011, in Andorra, has shown that Switzerland emerged as the number one most attractive European country for travel and tourism, followed by Germany, and Austria, in third place. Holland, Luxemburg, Denmark and Finland took seventh, eight, ninth and tenth place, while Portugal bagged the 13th place respectively [11].

Tourism in the European Union increased by 7.2 % overall from 2000 to 2009, giving an average annual change rate of 0.8 %.

The main beneficiaries of the upswing in tourism over the period 2004–09 were regions from Poland, Lithuania, Bulgaria, Greece and the United Kingdom. In the regions of Western Europe (mainly coastal regions) and Scandinavian countries, campsites are more frequently used as accommodation than in central and Eastern Europe.
Nine Member States were on the list of the top 20 tourist regions visited by foreign tourists: Spain, France, the United Kingdom, Italy, Austria, Greece, Cyprus, Portugal and the Czech Republic [10].

Table 1. Total number of trips by main mode of transport used in 13 EU countries

geo time	2000	2001	2002	2003	2004	2005	2006	2007	2008
be Belgium	1706.18	1706.18	1474.02	1887.73	1643.60	1585.56	1692.65	2078.34	2340.67
Denmark	1527.00	1474.90	1562.10	1626.70	1513.70	1509.50	1687.10	1724.26	2132.75
Germany	2180.00	2730.00	3030.00	3349.00	3197.00	2788.00	2866.00	2932.00	2994.09
Greece	456.89	391.21	385.56	419.76	455.70	377.37	383.28	781.50	794.82
Spain	2272.63	2881.20	2326.47	3545.69	3209.88	3285.45	3527.61	4205.74	6424.32
France	8949.34	8923.82	8681.00	9387.00	8793.00	8615.00	8640.00	9760.00	10444.98
Italy	5505.02	5462.46	6118.20	5990.82	6064.30	5786.19	6435945	7051.97	7649.65
Luxembourg	148.00	184.00	188.00	228.00	214.00	245.00	228000	256.00	281.00
Netherlands	3310.00	3310.00	3359.00	3545.00	3680.00	3599.00	3982000	4331.00	4592.00
Austria	1434.81	1434.81	1618.03	1864.86	1535.67	1500.19	2275364	2349.79	2123.33
Portugal	498.79	508.78	583.71	581.19	601.37	671.85	538646	896.90	873.27
Finland	999.00	968.00	1108.00	1255.00	1308.00	1221.00	1233.00	1505.00	1549.00
UnitedKingdom	1910.00	2100.00	2330.00	3190.00	3460.00	3350.00	3370.00	3320.00	3320.00

Source: [10], Eurostat/JP: Tourism statistics at regional level

2. METHODOLOGY

2.1. Association models

We consider six of the most commonly used association models. These are:

1. The model of Independence or the null association models which holds that there is no relationship between the variables which are also symbolized by (O). The log-linear model is: Log $(F_{ij}) = \lambda+\lambda_{A(i)}+\lambda_{B(j)}$, where log denotes the natural logarithm, F_{ij} the expected frequencies under the independence model, $\lambda_{A(i)}$ are the rows main effect and $\lambda_{B(j)}$ are the columns main effect [2, 3].
2. The Uniform association model, which is symbolized as (U) in log-linear form is $\log(F_{ij})=\lambda+\lambda_{A(i)}+\lambda_{B(j)}+\varphi\chi_i y_j$, where φ ιs a single parameter for interaction and χ_i ,y_j are the scores for the row and column variables (i =1,…,I, j =1,…,J) respectively.

3. The row effects model (R) where linear-by-linear interaction holds gives log $(F_{ij}) =\lambda+ \lambda_{A(i)}+ \lambda_{B(j)}+ \varphi\mu_I y_j$, where y_j are fixed scores for the column variable (j = 1,…, J) and μ_I are unknown scores for the row variable (I=1,…,I).

4. The column effects model (C) is the same as the R model with a change in subscripts: $\log(F_{ij}) = \lambda+\lambda_{A(i)}+\lambda_{B(j)}+\varphi\nu_j x_I$, where x_I are fixed scores for the row variable (i =1,…,I) and ν_j are unknown scores for the column variable (j =1,…,J).

5. The model that allows both row and column effects in additive form is called the R+C model, Goodman [6, 8]. The log-frequency version of the above model is: $\log(F_{ij}) = \lambda+\lambda_{A(i)}+ \lambda_{B(j)}+ \sum_{\kappa=1}^{I-1}\beta_\kappa y_j Z_{A(\kappa)} + \sum_{\kappa=1}^{J-1}\gamma_\kappa \chi_i Z_{B(\kappa)}$, where χ_i ,y_j are the scores as defined earlier, and $Z_{A(i)}$, $Z_{B(j)}$ denote indicators variables (or dummy variables) for the row levels and column levels, respectively.

6. The model, instead of additive row and column effects on the local odds ratios has multiplicative effects called the RC model or model II, [7]. The log-multiplicative model is: log (F_{ij}) = $\lambda+\lambda_{A(i)}+\lambda_{B(j)}+\varphi\mu_I\nu_j$, where the row score parameters μ_I and column score parameters ν_j are not known, but those estimated from the data.

2.2. Analysis of the models

Table 2. The model analysis

Models	(Likelihood)X^2	(Likelihood)G^2	Degrees of Freedom	Index of Dissimilarity	Final Iteration	Maximum Deviation
O	9118.36170	8901.94052	96	0.04222	3	0.00000000
U	7299.26409	7001.81921	95	0.03533	6	0.00030787
R	5193.27525	5170.96683	84	0.03261	7	0.00034554
C	5624.80225	5431.70723	88	0.02801	6	0.00028511
R+C	3626.37092	3626.12169	7	0.02597	7	0.00048455
RC	4449.21525	4304.59330	77	0.02507	924	0.00099371

We aim at finding out the model (out of the six) that best fit from the other models which we are examining, i.e., the total number of trips by main mode of transport used in 13 EU countries for the period of 2000-2008. For this reason, we are going to examine first the Index of Dissimilarity (L2), which shows that, the lesser the number, the more our model will give the best fit to match the total number of trips by main mode of transport used in 13 EU countries compared with other models under consideration.

2.2. Analysis of the models

We analyzed the six association models, used the data describe above, with the help of the statistics package CDAS [4]. We used the Pearson chi-squared (X^2) statistic, the likelihood-ratio chi-square (G^2) statistic, the index of dissimilarity $D = \sum_{ij} \left| f_{ij}/n - F_{ij}/n \right| / 2$ (where f_{ij} the observed frequencies and F_{ij} the expected frequencies (under the model) and we have the following results:

Table 3. Index of Dissimilarity

Models	**Index Of Dissimilarity(D)**
1. Null Association-Independence Model (O)	0.04222
2. Uniform Association Model (U)	0.03533
3. Row-Effects Association Model (R)	0.03261
4. Column-Effects Association Model (C)	0.02801
5. Row+Columns Effects Association Model (R+C)	0.02597
6. Row Column Effects Association Model (RC)	0.02507

At first sight it seems that the row-column model adjusted better to the gross operating surplus and mixed income in the years under study, as it is the one that has the lowest index of dissimilarity with D = 0.02507.

Authentically, we can prove this in another way through the calculation of Indicator BIC (**Bayes Informative Criterion**) [1]. The term for his calculation is:
The formula for this calculation is:

BIC = G^2 – (d.f.) Log(n)

Symbols:

n = the size of the sample

d.f. = degrees of freedom of the models

$G^{2=}$ the likelihood-ratio chi-square statistics

When comparing a number of models, then the model with the smallest value of BIC is the best. So we choose the models, those whose INDEX OF DISSIMILARITY are similar and the lowest out of the six models. However, since we have models with similar lower ratio, to justify which model give the best fit to match the both Countries and Years, the

calculation of the Index BIC (Bayes information criterion) gives the solution [12]. More precisely, the 4th, 5th and 6th model, hence, we see:
For n = 798159.89 and

Log (n) = Log (798159.89) = 13.59006422

In continuation we calculate the index for:

4° Model**:** BIC = G^2 – (d.f.) Log(n) = 5431.70723– (88 * 13.59006422) = 4235.78157864

5° Model: BIC = G^2 – (d.f.) Log(n) = 3626.12169 – (77 * 13.59006422) = 2579.68674506

6° Model: BIC = G^2 – (d.f.) Log(n) = 4304.59330 – (77 * 13.59006422) = 3258.15835506

From the calculations we could see that the best model is the 5th. In other words the row + column effects model (R+C).

2.3 Analysis of the association model

Afterwards, we control the models to see whether any of them is acceptable. Control is being done with the likelihood-ratio chi-square statistic G^2 and with the use of X^2 distribution. In the case of X^2 distribution Statgraph program will be of good help.
Firstly, the likelihood-ratio chi-square statistic for the Independence model (O) is G^2 = 8901.94052 with 96 degrees of freedom (d.f.). (The 95th percentile of the reference chi-square distribution is 120.017). So, the model of independence (O) is rejected because has much bad fit since the X^2 distribution is much smaller than the likelihood-ratio chi-square statistic G^2.
In continuation the Uniform association model is G^2 = 7001.81921 with 95 degrees of freedom (d.f.). (The 95th percentile of the reference chi-square distribution is 118.894). As it could be noticed this statistics is not accepted and does not have a satisfactory fit (adaptation) since the X^2 distribution is much smaller than the likelihood-ratio chi-square statistic G^2.
The likelihood-ratio chi-square statistic G^2 for the R model is reduced dramatically and is = 5170.96683 with 84 degrees of freedom (d.f.). (The 95th percentile of the reference chi-square distribution is 106.556). Also we observe that the model has a very bad fit (adaptation) because the X^2 distribution is much smaller than the likelihood-ratio chi-square statistic G^2.
The C model (years) has G^2 = 5431.70723 with 88 degrees of freedom (d.f.). (The 95th percentile of the reference chi-square distribution is 111.08) We therefore conclude also that this model show even the worst fit since the X^2 distribution is very much smaller than the likelihood-ratio chi-square statistic G^2.
Moreover, the statistics of the model R+C, that takes into account the effects for both the macroeconomic analysis and years in additive form, is G^2 = 3626.12169 with 77 degrees of freedom (d.f.). (The 95th percentile of the chi-square distribution is 98.6146). Similarly this model has a bad fit (adaptation), because the X^2 distribution is very much smaller than the likelihood-ratio chi-square statistic G^2.
Finally the model of row-column effects in multiplicative form (RC), has G^2 = 4304.59330 with 77 degrees of freedom (d.f.). (The 95th percentile of the reference chi-square distribution is 98.6146). Again the Statistics is reduced dramatically just as the previous model because they have the same d.f, but is shown to remain unacceptable fit since the X^2 distribution is very much smaller than the likelihood-ratio chi-square statistic G^2.
However, we have to realise and in which degree of influence it has on each model. In order to verify this we will have to construct the table of Analysis of association (ANOAS).

2.4. Analysis of Association Table (ANOAS)

The ANOAS table was given by Goodman [9]. In this table the chi-squared are the partitioned as sums of square in a two-factor analysis of variance using the likelihood. The ANOAS table partitions the effects on association show the percent of the likelihood-ratio chi-square statistic G^2 (O) for basic (null) model of independence that measures the total divergence of the variables. In other words, we can find the percentage of baseline chi-squared X^2 distribution, which influences each of our model's phenomenon that we study.
The analysis of association table has the following differences of our models: O-U is the total effects model, U-C are the column effects model, C-RC are the column effects model that gives the effect of columns and RC are the residuals of the models.

Table 4. The ANOAS table

Effects	Model used	G^2	D.F	Percentage
1. General	O-U	1900.12131	1	21.35%
2. Rows	U-C	1570.11198	7	17.64%
3. Columns	C-RC	1127.11393	11	12.65%
4. Residual	RC	4304.59330	77	48.36%
Total	**O**	**8901.94052**	**96**	**100.00%**

As shown from the ANOAS table above, the uniform effects are very weak because the U model accounts for less than 21.35% of the baseline chi-squared value. The row effects are weak because the R model accounts for only the 17.64% of the baseline chi-squared X^2 distribution value. The column effects are very weak because the C model accounts for only 12.65% of the baseline chi-squared value. Finally, the residual model RC accounts for only 48.36%. Moreover, because our best model (R+C) show bad fit (not accepted), it is supposed that we should proceed to examining the multivariate models.

3. THE MULTIVARIATE MODEL

In the RC (M) association model, M represents the dimension fit to be, which is utilized by PROGRAM RCDIM. As shown below the multivariate model RC (M=8) is the acceptable model with the best fit.

The results are as follows:

Table 5. Multivariate model

Models	*RC(5)*	*RC(6)*	*RC(7)*	*RC(8)*
X^2	120.12010	36.54936	12.79289	0.00000
G^2	120.28671	36.50028	12.79029	0.00018
d.f.	21	12	5	0
D	0.00273	0.00118	0.00069	0.00000

Model RC (5) multivariate row, column, M=5, Model RC (6) multivariate row, column, M=6
Model RC (7) multivariate row, column, M=7, Model RC (8) multivariate row, column, M=8

3.1. Examining of the multivariate model

The model RC (5) with M=5 has likelihood-ratio chi-square statistic G^2 = 120.28671 with 21 degrees of freedom (d.f.). The 95th percentile of the reference chi-square distribution is chi-squared X^2 distribution is 120.12010. We could conclude therefore that this model has a bad fit because the X^2 distribution is much smaller than the likelihood-ratio chi-square statistic G^2.
Moreover, the model RC(6) with M=6 has likelihood-ratio chi-square statistic G^2 = 36.50028 with 12 degrees of freedom (d.f.). The 95th percentile of the reference chi-square distribution is 36.54936. This model has has a satisfactory fit because the X^2 distribution is bigger than the likelihood-ratio chi-square statistic G^2.
The Model RC(7) with M=7, has likelihood-ratio chi-square statistic G^2 = 12.79029 with 5 degrees of freedom (d.f.). The 95th percentile of the reference chi-square distribution is 12.79289. Again, we observe that the model has has a satisfactory fit because the X^2 distribution is bigger than the likelihood-ratio chi-square statistic G^2.
Finally, the model RC (8) with M= 8, has likelihood-ratio chi-square statistic G^2 0.00018 with 0 degrees of freedom (d.f.). In this case the 95th percentile of the reference chi-square distribution is 100 after the likelihood-ratio chi-square statistic G^2 has a 0.00000 tendency with 0 degrees of freedom (d.f.). Here we see that the multivariate model RC with M=8 has a perfect fit. We observe also that model M=8 covers {(8901.94052 – 0.00018) / 8901.94052} of = 100% of the total data.
Because the model with the smaller M, if it is satisfactory gives the better explanation of interaction of rows and columns, we will prefer model M= 8 that has perfect fit.

3.2. Estimation of the multivariate model

The expected frequencies under the independent and row effects models for the total number the total number of trips (absolute value/unit) by main mode of transport used in 13 EU countries of are given below:
Note: The row effects model seems to give much better fit, particularly at the end of nominal scale.

Countries (Row)	Years (Column)	Data	Expected values of Model (0) F_{ij} 1	Expected values of RC(M=8) F_{ij} 2
1	1	1706.1800	1367.0246	1706.1800
2	1	1527.0000	1251.9175	1527.0000
3	1	21800.0000	22111.8008	21800.0000
4	1	456.8900	377.1393	456.8900
5	1	2272.6300	2689.4525	2272.6300
6	1	8949.3400	6972.5038	8949.3400
7	1	5505.0200	4755.9243	5505.0200
8	1	148.0000	167.2842	148.0000
9	1	3310.0000	2859.4394	3310.0000
10	1	1434.8100	1368.8841	1434.8100
11	1	498.7900	488.1533	498.7900
12	1	999.0000	945.5118	999.0000
13	1	19100.0000	22352.6246	19100.0000

As seen from the table above, the values/prices of the model RC(M = 8) show how they fit better in the data.

Finally, in order to realise the degree of association (correlation) which exists between the countries and years (row and column models), we use θ (Theta) of the second model, the (uniform association U) in order to calculate the indicator of innate association – i.e. **φ** (phi)**.**

THETA (FOR THE MODEL II) = 1.00443

We observe that the price of θ (Theta) is in the price of 1, which means that we have independence association (correlation) between the 13 EU countries.

The odds ratio is θ (Theta) = 1.00443. The parameter of interaction is φ (phi) = φlnθ = ln (1.00443) = 0.00442. The **φ** (phi) **½ =** √0.00442 = 0.0665

Based on the result, we can see that the relationship between the 13 EU countries and the years are slightly positive. In other words, there is no change in the relationship between the 13 EU countries over these years (the change is about 0.07%). In other words, the correlation is zero (independence).

5. SUMMARY AND CONCLUSION

All the six association models show bad fit. The column effects model (years) are weak because it covers only 12.65% of the data. The multivariate model RC (M= 8) gives the best fit.

The estimated effects for the total number of trips by main mode of transport used in 13 EU countries are:

Belgium: $\hat{\tau}_1$ = ln(0.377349) = -0.974585

Denmark: $\hat{\tau}_2$ = ln(0.462013) = -0.772162

Germany: $\hat{\tau}_3$ = ln(2.409193) = 0.879292

Greece: $\hat{\tau}_4$ = -ln(1.699264) = -0.530195,

Spain: $\hat{\tau}_5$ = ln(0.261676) = -1.340648

Italy: $\hat{\tau}_7$ = ln(0.873182) = -0.135611

Luxembourg: $\hat{\tau}_8$ = -ln(2.485100) = -0.910313

Netherlands: $\hat{\tau}_9$ = ln(0.363599) = -1.011704

Austria: $\hat{\tau}_{10}$ = -ln(0.384853) = 0.954894

Portugal: $\hat{\tau}_{11}$ = -ln(1.419529) = -0.350325

France: $\hat{\tau}_6$ = ln(1.259433) = 0.230662 Finland: $\hat{\tau}_{12}$ = -ln(0.748218) = 0.290061

United Kingdom: $\hat{\tau}_{13}$ = ln(2.403235) = 0.876816

We now compare 13 EU countries with each other for the total number of trips by main mode of transport used. For instance, if we compare Spain with Greece, we see that: $\hat{\tau}_5 - \hat{\tau}_4$ = -0.8105, exp(-0.8105) = 0.44464. This means that Spain had 0.44464 fewer trips per 100.000 tourists than Greece.

In the case of Mediterranean countries, France and Italy we find out that $\hat{\tau}_6 - \hat{\tau}_7$ = 0.366273, exp(0.366273) = 1.44235. This means that France had 1.44235 more trips per 100.000 tourists than Italy.

The difference in the total number of trips between Germany and England are: $\hat{\tau}_3 - \hat{\tau}_{13}$ = 0.00248, exp(0.00248) = 1.00248. It means that Germany had 1.44235 more trips per 100.000 tourists than England.
Even among the advanced countries of Europe there are differences in the number. Specifically between Luxembourg and Denmark $\hat{\tau}_8 - \hat{\tau}_2$ = -0.13815, exp(-0.13815) = 0.87097, we find out that Luxembourg had 0.87097 fewer trips per 100.000 tourists than Denmark.

Finally, comparing the total number of trips between the Netherlands and Finland, we see that $\hat{\tau}_9 - \hat{\tau}_{12}$ = -1.30177, exp(-1.30177) = 0.27205, this means that the Netherlands made 0.27205 fewer trips than Finland.
Generally, in conclusion we find out that the multivariate model RC (M= 8) gives the best fit among all. However, to be more precise, the percentage of trips with the most common means of transport by 100.000 tourists is influenced by several factors. These may be due to:

- the standard of living of each country
- the geographical location of each country
- government spending on tourism and
- various other factors that are difficult to be identified or determined.

Moreover, we can easily see from the above data showing the total number of trips by main mode of transport used in 13 EU that over the years the rate of tourism increased due to improved economic conditions [5].

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