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FORECASTING INTERNATIONAL TOURISM DEMAND: THE EVIDENCE OF MACEDONIA

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Abstract:
The paper makes an attempt to provide estimation of foreign tourism demand by 2014, by investigating the case of Macedonia. The author applies the Box-Jenkins methodology and tests several alternative specifications in the modeling of original time series. Upon the outcomes of standard indicators for accuracy testing, the research identifies the model of ARIMA(1.1.1) with a dummy, as the most appropriate. According to the four-year-forecasts, it is expected a 25% increase of the international tourist arrivals. Although the suggested model cannot explain the driving factors behind the results, the projected values can assist in mitigating the potential negative impacts as well as in the preparation of tourism development plan in Macedonia.

Key words: forecasting, Box-Jenkins methodology, international tourism demand, Macedonia.

INTRODUCTION

As one of the most dynamic world industries, tourism is facing numerous challenges which affect its development. In order to cope with them, the planers and policy-makers apply the process of forecasting as the only way to furnish information, which permit them to reach decisions before the occurrence of certain events. In order to create a comprehensive tourism development plan as a base for formulating tourism policy, reliable estimates of future demand must be undertaken. However, that is not a trouble-free process due to numerous dissimilarities which prevail to tourism industry. So, the main aim in introducing forecasting process in tourism is to envisage success of the destination by ensuring that visitors are hosted in a way that maximizes the benefits to stakeholders with minimum negative effects, costs, and impacts (Wilkinson 1997; Mason 2003; Goeldner and Ritchie 2006; Edgell et al. 2008).

There is a wide range of factors which can influence tourism demand. Most often, they can be detected within the tourism-generating countries (Lickorish and Jenkins 1997). Nevertheless, the tourism demand affects all sectors of an economy - individuals and households, private businesses and the public sector (Sinclair and Stabler 1997; Stabler, Papatheodorou, and Sinclair 2010). In this respect, each country is interested in

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developing tourism since it generates various positive impacts, in the first line economic ones. So, estimating tourism trends may be the only way in reducing the risk of decisions for future tendencies, as well as representing a key determinant of business profitability (Frechtling 2001; Song and Turner 2006). In the same line, predicting tourism demand is important to the tourism manager and to those that depend on that manager, since more accurate estimations reduce the risks of decisions more than do less accurate ones.

Generally, the contribution of this paper lies in the fact that it enriches the poorly-developed empirical academic work within this scientific area in Macedonia. Moreover, this research contributes to alarming relevant tourism-actors that the varieties of changes that influence tourism often cannot be envisaged (Petrevska 2011), so the application of forecasting methods is fully justified. Additionally, this empirical investigation may serve as a reminder that only if being prepared in due time, one may struggle the unexpected challenges.

LITERATURE REVIEW

Forecasting tourism demand has attracted much interest in academia, and practitioners as well. The vast majority put an accent on the application of different techniques, both qualitative and quantitative, to forecast tourism demand in various destinations. According to Witt and Song (2000) and Li, Song and Witt (2005), the performance of the forecasting models varies upon various factors, like: data frequencies used, the destination-origin country/region pairs under consideration, the length of the forecasting horizons etc. So, the overall conclusion is that no panacea can be introduced to tourism demand forecasting.

A variety of econometric models are applied. Some are concentrated on the identification of the relationships between tourism demand and its influencing factors, while others evaluate the forecasting performance of the econometric models in addition to the identification of the causal relationships. In this line, according to the comprehensive study of Song and Li (2008) the forecasting methodology is very diverse since the researches employ both, the time series and econometric approaches in estimating tourism demand.

Although the basic variable in determine tourism demand has gradually modified, the tourist arrivals is still the most applicable one. It is noticeable that many authors, decomposed this variable further in more in-depth manner into holiday tourist arrivals, business tourist arrivals, tourist arrivals for visiting friends and relatives purposes (Turner and Witt 2001a, 2001b; Kulendran and Wong 2005), tourist arrivals by air (Coshall 2005; Rosselló 2001), tourist expenditure in the destination (Li et al. 2004, 2006a and 2006b) tourist expenditure on particular tourism product categories as meal expenditure (Au and Law 2002), sightseeing expenditure (Au and Law 2000), and shopping (Law and Au 2000). Other tourism demand variables used in the literature include tourism revenues (Akal 2004), tourism employment (Witt, Song, and Wanhill 2004) and tourism import and export (Smeral 2004).

Regardless the applied model, the accuracy is the one of the most important forecast evaluation criterion (Witt and Witt 1992). Namely, it is expected that the final model chosen for forecasting would produce projections that are as precise as possible. However, it is not always the case due to data limitations, measurement errors, unclear picture for the system of tourism demand etc. (Song and Witt 2000).

Even when an ideal forecasting model can be identified, it can only serve as an approximation for complex tourists' behavior, for it is possible that tourists' decisions change reflecting the changes in preferences, motivation or economic shocks. Hence, the planner should always be prepared to make a revision to the previously identified and defined model, to the newly created changes.

METHODOLOGY

The research is based on application of the Box-Jenkins methodology (Box and Jenkins 1976). It is a quantitative method which is commonly applied in forecasting, known as autoregressive integrated moving averages (ARIMA) models. It is a time series model that explains a variable with regard to its own past and a random disturbance term. Particular attention is paid to exploring the historic trends and patterns (such as seasonality) of the time series involved, and to predict the future of this series based on the trends and patterns identified in the model. Since time series models only require historical observations of a variable, it is less costly in data collection and model estimation. As one of the most popular linear models for forecasting time series, it enjoyes great success in academic research (Qu and Zhang 1996; Law and Au 2000; Law 2004; Goh and Law 2002; Kulendran and Shan 2002; Huang and Min 2002; Lim and McAleer 2002; Coshall 2005).

So, the objective of this research is to forecast tourism demand in Macedonia in terms of international tourist arrivals by introducing the ARIMA models. In order to fulfill its main aim, the paper is based on available sources of secondary data being processed by the software E-views version 6.0. So, the author models the original time series - the number of foreign tourists in Macedonia in the period 1956–2010, thus having a sample consisted of 55 observations.

ANALYSIS, RESULTS AND DISCUSSION

Given that the basic assumption for applying the Box-Jenkins methodology is obtaining stationarity of the time series, the first step in the analysis is to perform the stationarity test. The visual inspection of the time series movement in a particular period is the easiest approximate way in evaluating its stationarity.

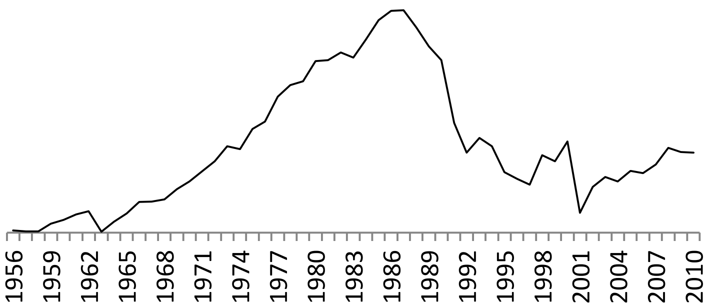

Figure 1. International tourist arrivals in Macedonia, 1956–2010

The Figure 1 (State Statistical Office, 2011) reveals that the international tourist arrivals shows extremely upper trend in the period 1956–1987, and then, in the next twenty years, it shows sharp downward trend. A slight increase followed by an upper trend line is present from the beginning of 2002 until 2008, which is the last observation in the analyzed time interval. Hence, visually, one can observe two pronounced trends in the movement of the time series, so some of its characteristics imply non-stationarity. Therefore, based on the Chart 1, it is obvious that the series has different average values in the separate subsets of the sample period. In the same line, it is noticeable that the time series variance is not constant in all sub-periods of the sample. However, for precautionary reasons, this intuitive conclusion is tested by appropriate quantitative criteria. In that respect, the correlogram of the series is used, showing the autocorrelation function (ACF). It is sufficient to employ only one third of the total number of the sample observations, when calculating the autocorrelation coefficients (ρ_k). Hence, the ACF is calculated for 18 lags.

Table 1. Correlogram of the international tourist arrivals

Lags (k)	ACF (ρk)	LB-statistics	p-value
1	0.947	50.258	0.000
2	0.874	93.897	0.000
3	0.784	129.73	0.000
4	0.685	157.62	0.000
5	0.579	178.02	0.000
6	0.467	191.54	0.000
7	0.359	199.69	0.000
8	0.255	203.91	0.000
9	0.157	205.55	0.000
10	0.059	205.79	0.000
11	-0.053	205.98	0.000
12	-0.154	207.66	0.000
13	-0.252	212.31	0.000
14	-0.346	221.28	0.000
15	-0.423	234.98	0.000
16	-0.486	253.62	0.000
17	-0.527	276.07	0.000
18	-0.545	300.80	0.000

From the Table 1, the following conclusions can be made:

(1) The correlogram starts with very high correlation coefficient of 0.95;

(2) Autocorrelation coefficients slowly decay; and

(3) There is a highly expressed autocorrelation in the series even for several lags, e.g., the autocorrelation coefficient at the sixth lag is still high and is almost 0.5.

All this clearly emphasizes that the series is non-stationarity, because for stationarity series the autocorrelation coefficients of all pairs of observations are equal to zero. However, in order to draw a solid conclusion for the reliability of the calculated autocorrelation coefficients, it is necessary to check their statistical significance, i.e. to see whether the calculated autocorrelation coefficients of the sample really represent the true autocorrelation coefficients of the population. As stated in the statistical theory, if dealing with a random process, than the autocorrelation coefficients are approximately characterized by the normal distribution, with a zero mean and variance of 1/*n*, where *n* is the sample size (Gujarati 1995, 717).

In that respect, the standard error of the autocorrelation coefficient is calculated by using the following formula: s.e. = $\sqrt{\frac{1}{n}}$

In our case, the standard error is: √1/53 = 0.137.

According to the table for normal distribution, we can calculate the 95% confidence interval for the autocorrelation coefficients:

Confidence interval = ± 1.96 x 0.137 = ± 0.269.

If the calculated autocorrelation coefficient lies within the confidence interval, it means that the null hypothesis that the true autocorrelation coefficient of the population is zero (H_0: $\rho_k = 0$), cannot be rejected. From Table 1, it can be seen that the first seven autocorrelation coefficients are statistically significant, i.e. different than zero, the coefficients from lag 8 until lag 13 lie within the confidence interval, and then, the coefficients are again different than zero. The large number of statistically significant coefficients confirms that the series is non-stationarity.

However, given the problems with individual testing of the significance of autocorrelation coefficients, the joint hypothesis that all autocorrelation coefficients are equal to zero, is tested. This test is usually made with Ljung-Box statistic (LB), calculated with the formula:

$$LB = n(n+2)\sum_{i=1}^{k}\frac{\rho_i^2}{n-i} \quad (1)$$

The LB-statistics tests the null hypothesis that there is no autocorrelation for all coefficients at certain number of time lags. Further on, if the null hypothesis is true, the LB-statistics asymptotically follows the χ^2 distribution with degrees of freedom equal to the number of autocorrelation coefficients. The values of LB-statistics are presented in Table 1. It can be concluded that for all time lags, the LB-statistics by far exceeds the critical values. For instance, even at 13 lags, the LB-statistics is statistically highly significant (300.8). In that respect, this test shows that the null hypothesis can be rejected, which by all means is a proof that the analyzed time series is non-stationarity.

Yet, when interpreting the LB-statistics it should be cautious for the following reason: it was mentioned that some of the autocorrelation coefficients, when tested individually, are statistically significant, while the others are insignificant. In this case, it is known that the LB-statistics has low power, because the significant coefficients can be neutralized by the insignificant ones. Hence, the evidence gained by the LB-statistics is additionally tested by employing two unit root tests: the Augmented Dickey-Fuller (ADF) and the Phillips-Perron test (PP).

Table 2. Stationarity test

Test	constant	constant + trend	none
ADF	-1.547875 (0.5016)	-1.498094 (0.8174)	-0.511774 (0.4899)
PP	-1.599661 (0.4756)	-1.496664 (0.8182)	-0.557843 (0.4708)

In the first row of Table 2, the values of the ADF-test are shown in its three variants, and in all cases, the null hypothesis for the presence of unit root, cannot be rejected. Consequently, this test suggests that the series is non-stationarity. However, as stated previously, in the beginning of the 1990s, there is a presence of a structural break in the series. In that case, it is known that the ADF-test has low power and, hence, the results are checked with the PP-test. As shown in the second row of Table 2, all the variants of the PP-test show that the null hypothesis of a unit root cannot be rejected. Hence, this test, too, suggests that the series is non-stationarity. As mentioned previously, if the time series is non-stationarity, than the Box-Jenkins methodology cannot be applied. It means that it is necessary to transform the series in order to make it stationarity, which is done by differencing the original series.

Table 3. Correlogram of the international tourist arrivals (First differences 1956–2010)

Lags (k)	ACF (ρ_k)	PCF (ρ_{kk})	LB-stat.	p-value
1	0.256	0.256	3.5980	0.058
2	0.208	0.153	6.0355	0.049
3	0.150	0.073	7.3325	0.062
4	0.078	-0.000	7.6874	0.104
5	0.100	0.053	8.2802	0.141
6	-0.059	-0.123	8.4935	0.204
7	-0.110	-0.114	9.2448	0.236
8	0.024	0.093	9.2823	0.319
9	0.047	0.086	9.4246	0.399
10	0.199	0.207	12.078	0.280
11	-0.122	-0.247	13.103	0.287
12	-0.044	-0.058	13.242	0.352
13	-0.026	-0.038	13.290	0.426
14	-0.168	-0.162	15.375	0.353
15	-0.091	0.005	16.002	0.382
16	-0.260	-0.128	21.283	0.168
17	-0.170	0.000	23.602	0.131
18	-0.051	-0.001	23.819	0.161

When the series is differenced, one cannot observe some regular movement of the autocorrelation coefficients, which begin with low values, decreasing quickly to zero, and then moving in a wave-style, i.e. increasing and decreasing. Also, one can observe the great value of the autocorrelation coefficient at lag 10. It can be explained with the fact that the series declines sharply twice with an interval of 10 years (the collapse of Yugoslavia in 1991, and the war in Macedonia, in 2001). In order to check the stationarity of the differenced series, the autocorrelation coefficients are individually tested with the confidence interval, which in this case is $\pm$ 0.272. Further on, it was shown that the null hypothesis that the true autocorrelation coefficients of the population are equal to zero cannot be rejected. Namely, the value of LB-statistic with 18 degrees of freedom is 23.819, which is not sufficient to reject the null. By all means, the above results show that by differencing of the original time series, stationarity is obtained. Yet, once again, in order to verify the results, the ADF-test and the PP-test are used. From Table 4, it can be concluded that the values of the statistics are highly significant, so once again, we can conclude that the differenced series is stationarity.

After performing the additional tests, it can be concluded the Box-Jenkins methodology can be applied. The first step is to identify the appropriate model that will explain the time series movement. Here, crucial instruments are the sample autocorrelation (ACF) and partial autocorrelation (PACF) functions. The detailed analysis of both functions (presented in Table 3) did not show any regularity in the movement of the autocorrelation coefficients (slow decay, sharp picks at certain lags etc.), from which, the model could be identified. What the correlogram suggests is that we have a mixed process, i.e. combination of autoregressive (AR) and moving average (MA) processes.

Table 4. Stationarity test (First differences 1956–2010)

Test	constant	constant + trend	none
ADF	-5.376144 (0.0000)	-5.445010 (0.0002)	-5.415973 (0.0000)
PP	-5.466517 (0.0000)	-5.529348 (0.0002)	-5.503297 (0.0000)

Given the unclear character of the time series, several alternative specifications were used to model the original series: ARIMA(1.1.1), ARIMA(1.1.1) with dummy, ARIMA(2.1.2), restricted ARIMA(1.1.10) with dummy, and restricted ARIMA(10.1.10). All models represent the original time series in an adequate manner.

The ARIMA(1.1.1) model has low coefficient of determination and the MA term of the model is statistically insignificant. The ARIMA(2.1.2) model has a slightly higher coefficient of determination comparing to the previous model, but the second MA is marginally insignificant at 5%. Also, the inverted MA root is 1, which makes the process inappropriate for forecasting. The restricted ARIMA(10.1.10) model tracks the original time series quite well, both terms are highly significant and the coefficient of determination is twice higher comparing to the previous two models. However, the reciprocal root of the MA term is very near to 1. Yet, the main problem with this model refers to the economic interpretation of the two terms. Namely, the statistical significance of the AR and MA terms at 10 lags is a consequence solely of the effects of the structural breaks in 1991 and in 2001. Since there is no reason for these events to take place in future on regular basis (in the time interval of 10 years), the inclusion of these AR and MA terms will not ensure adequate forecasting in the future.

According to the statistical features of the models, two specifications out of five, show best results: the ARIMA(1.1.1) with dummy and the restricted ARIMA(1.1.10) with dummy. These models have the highest coefficients of determination and, also, they are favored on the basis of both the Akaike and the Schwarz information criteria. Further on, here, there are no problems with the inverted AR and MA roots. Yet, despite the positive statistical characteristics, the restricted ARIMA(1.1.10) with dummy is discarded due to the problems with the interpretation of the MA term. Once again, we emphasise that the inclusion of the MA term with a time lag of 10 periods ensures a good approximation of the time series in the past, but not in the future. Hence, only the results of the ARIMA(1.1.1) with a dummy are presented here, as the most appropriate model for forecasting the original time series.

From the Table 5, it can be concluded that the AR term is highly significant with value 0.8, which suggests a high level of persistence in the series. The second term is not significant at the level of 5%, but having in mind the relatively small sample, we decided to work with the model, because of its significance at 10%. In the same line, the coefficient before the dummy is highly significant. The adjusted R^2 is satisfactory high (0.64) having in mind that we have modeled the first difference of the series. The values of the inverted roots of the AR and MA terms lie within the unit root, which, once again, confirms that the chosen model is appropriate. Finally, as stated above, according to the information criteria, this model has better performances comparing to the previous ones.

Table 5. ARIMA(1.1.1) model

Dependent Variable: International tourist arrivals (First differences)				
Method: Least Squares				
Sample: 1958-2010 (53 observations)				
Variable	Coefficient	Std. Error	t-Statistic	Probability
DUMMY	-191192.4	21341.93	-8.958533	0.0000
AR(1)	0.787363	0.165950	4.744591	0.0000
MA(1)	-0.423157	0.241562	-1.751749	0.0862
R^2	0.650544	Akaike info criterion		23.66973
Adjusted R^2	0.635984	Schwarz criterion		23.78337
S.E. of regression	32448.72	Durbin-Watson statistics		2.089552
Inverted AR roots 0.79				
Inverted MA roots 0.42				

Due to the fact that the primary purpose of building a forecasting model is to clearly discern the future of a phenomenon, the most important criterion is how accurately a model does this. It means to make an effort to disentangle how closely the estimations provided by the model conform to the actual events being forecasted. In this respect, we support the accuracy of the suggested model by the within-sample forecasts. So we employ some of the standard indicators, like: the Mean Absolute Percentage Error (MAPE), the Theil Inequality Coefficient (TIC), the Bias proportion, the Variance proportion and the Covariance proportion.

The MAPE indicator can be used in comparing errors in forecasting the time series expressed in different values, thus expressing it in percent of the values of the original series. Upon the equation 2, the MAPE of the forecasts is 9.26%, which indicates excellent forecasting patterns of the suggested model.

$$MAPE = \frac{1}{h}\sum_{t=T}^{T+h}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \tag{2}$$

The TIC is also used for comparing errors in forecasting the time series expressed in different values. Specifically, this coefficient builds on the root means squared error and its value lies between 0 and 1. In our case, based on equation 3, the TIC is 0.043 which gives us additionally encouragement for justification of the suggested model.

$$TIC = \frac{\sqrt{\frac{1}{h}\sum(\hat{y}_t - y_t)^2}}{\sqrt{\frac{1}{h}\sum\hat{y}_t^2} + \sqrt{\frac{1}{h}\sum y_t^2}} \tag{3}$$

The other standard indicators also are in our favor. Namely, with the Bias proportion of only 0.017, the Variance proportion of 0.029 and high Covariance proportion of 0.954, we strongly propose the ARIMA(1.1.1) model. The overall good performances of the chosen model allows for its application in forecasting tourism demand. Therefore, we proceed with estimation of the international tourist arrivals for the period 2011–2014. The forecasted values are presented in the Table 6.

Table 6. Forecasting tourism demand in Macedonia by ARIMA(1.1.1) model

Years	2011	2012	2013	2014
International tourist arrivals	290 922	298 214	303 956	308 477

The results of the dynamic forecasts of the tourism demand in Macedonia using the ARIMA(1.1.1) with a dummy, point out that in the period 2011–2014, the international tourist arrivals will increase for about 10 000 tourists in the beginning years, and then a moderate growth can be expected, leading to the forecast of 308 477 foreign tourists in 2014. So, according to the model, it is expected the international tourism demand to mark increase of 4–6%. The forecasts are in the line of the the updated analyses of the world leading tourism experts which confirm confidence weakening, but still with positive patterns. Namely, it is expected that Europe will mark a moderate upward trend of 2–4% in the forthcoming years (UNWTO 2012, 6).

CONCLUSIONS

This research introduces the Box-Jenkins methodology for forecasting international tourist arrivals in Macedonia. From several specifications, according to the accuracy outcomes, the paper suggests the model of ARIMA(1.1.1) with a dummy. So, upon this model a medium-run estimation of foreign tourism demand for Macedonian destinations is provided.

Additionally, the paper explains that the implemented model does not provide 'the' solution, but only assists in finding it. Even though the model results are essential elements in the preparation of well-coordinated policies, they cannot do the job all by themselves. The research outcomes may be presented only as a framework, while the rest needs to be fulfilled with a lot of common sense and knowledge of details. So, the forecasts cannot explain the factors behind these trends, but on the other hand may serve as a solid base for mitigating potential negative impacts and preparing tourism development plan in Macedonia. Despite the fact that there are varieties of changes in the surrounding which often cannot be envisaged, like financial crises, terrorist attacks, war conflicts and crisis, epidemics etc., the paper argues the justification of applying forecasting methods. The main aim is to be prepared in due time to cope with some future challenges. Finally, the forecasts predict that the upward trend will continue and until 2014, it can be expected a 25% increase of international tourist arrivals.

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