A Neural Network Model of the Impact of Political Instability on Tourism

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Abstract—This paper presents an empirical integration of the dimensions of political instability with traditional exogenous variables, which are usually employed in econometric tourism demand forecasting, within a tourism demand model in order to investigate causal relationships between political instability and tourism. The work uses the POLINST Database, which contains events of political instability from 1977 to 1997 that took place in the Middle East – Mediterranean region. The model is based on a Focused Tapped Delay Line Neural Network (FTDNN) with a sliding time window of 12 months. The evaluation results show that our model can be used to achieve a good estimation of the effects of political instability on tourism. In an extended set of experiments we were able to show the relative importance of the political instability factors on tourism. Finally, our model also allowed to estimated the time lag between a political instability/terrorist event and the reduction of tourist number to the destination.

I. INTRODUCTION

Terrorism and political instability in the Mediterranean is a particularly serious threat and continues to cause grave concern and disruption in many countries in the region. Fuelled by political tensions and economic and social disparities, it is utilised by extremist groups whose interests and networks often transcend national boundaries. In addition to its harmful effect on the security and stability of the countries of the broader Mediterranean basin, terrorism has a deleterious and destructive effect on the highly vulnerable tourism industry. The very narrow profit margins make it particularly sensitive to economic and political instability. Thus the result is a complex relationship between economics, politics, and political instability. Being able to adequately model and estimate the effects of political instability of tourism would be a valuable contribution toward minimising its negative effects.

A study by Patie and Snyder [1] on modelling tourism demand compared classical time series forecasting techniques with a neural network model with back-propagation algorithm. The forecast results from the different models showed that the Neural Networks and Census II models were the most accurate (using Mean Absolute Percentage Error –MAPE). However, despite the promising results of the neural network model it appeared that it was partly unable to capture the seasonality component of the visitor behaviour.

Law and Au [2] used a supervised feed-forward neural network and four other techniques to forecast Japanese tourist arrivals in Hong Kong. In comparison to the other forecasting techniques, the neural network demonstrated higher forecasting accuracy. Although this study has indicated the feasibility of applying a neural network model to practical international tourism demand forecasting its significance was undermined by the use of yearly data due to the unavailability of seasonal data.

Burger and his colleagues [3] compared a variety of time series forecasting methods to predict tourism demand for a certain tourism destination. More specifically their study has concentrated on forecasting the US demand for travel to Durban, South Africa over the period 1992 to 1998. The neural network model performed better than the other models - it achieved a very high r (0.979) and the lowest MAPE (5.07%). Burger et al. concluded that neural networks are significantly better than the traditional time series forecasting techniques since they are able to handle non-linear behaviour. Furthermore, their study also found that if the forecast period is exactly one year into the future the neural network model performs fairly well due to repetitions of expected similar seasonal patterns.

A number of other studies have discussed modelling the tourism demand, forming a well established set of demand measures (dependent variables) and economic-based determinants (independent variables) [4]-[7]. The work presented here extends the existing studies by attempting to integrate the dimensions of political instability within a tourism demand model in order to investigate empirically the cause and effect relationships between political instability and tourism in study of selected Mediterranean destinations.

II. DATA PRE-PROCESSING

The POLINST database [8] that was used in this study contains more than 7,200 daily chronological entries of political instability for the period 1977-1997 (aggregated and grouped in 228 monthly data records) for four countries in the Mediterranean: Cyprus, Greece, Israel, and Turkey. Each event is characterised by coded variables such as date, type of action, number of fatalities, number of injuries, geographical location, organisations involved and
bibliography of the sources from where the data was extracted.

For every country under examination (Cyprus, Greece, Israel and Turkey) the demand for travel was expressed as:

\[ Y = f(\text{INC}, \text{ER}, \text{PO}, \text{CPI}, F_{1 \text{pol}}, F_{2 \text{pol}}, F_{3 \text{pol}}, \ldots, F_{7 \text{pol}}) \]

where

- \( Y \) = tourism demand: the number of tourist arrivals in destination X
- \( \text{INC} \) = average per capita income of tourists for five major European tourism generating countries
- \( \text{ER} \) = the foreign exchange rate (national currency/US$)
- \( \text{PO} \) = price of oil
- \( \text{CPI} \) = Consumer Price Index at the destination as a proxy to the cost of living at the destination
- \( F_{1 \text{pol}}, \ldots, F_{7 \text{pol}} \) denote the factors of political instability that resulted from the analysis of POLINST dataset, presenting the number of different types of events.

The dependent variable (tourist arrivals) as well as the first four explanatory variables (Exchange Rate, Consumer Price Index, Price of Oil, Income) were normalised with respect to the mean value of each variable. Prior to the normalization, the change of the value since the last year was computed. The following equation was used for the normalization of the tourist arrivals \( Y^{i,j} \) for month \( i \) \((i = 1, \ldots, 12)\) in year \( j \) \((j = 1, \ldots, 21)\):

\[
Y_{i,j}^{\text{norm}} = \frac{Y_{i,j} - Y_{i,j-1}^{\text{mean}}}{Y_{i,j}^{\text{mean}}}
\]

where \( Y_{i,j}^{\text{mean}} \) is the average number of arrivals for month \( i \) \((i = 1, \ldots, 12)\). Analogous equations were used for the other four variables.

For the factors of Political Instability the normalisation procedure was based on the maximum value of each factor (variable) and reflected the absolute value of each variable for a particular month:

\[
F_{i,j}^{\text{norm}} = \frac{F_{i,j}}{F_{i,max}}
\]

where \( F_{i,max} \) is the maximum value of the political instability factor for month \( i \) \((i = 1, \ldots, 12)\).

The normalized data was used for training, validation and testing the neural network on the prediction of the number of tourist arrivals. The above normalization of the dependent variable tackles implicitly the problem of seasonality in tourism. The model deals with the change in the number of tourist arrivals for a particular month compared to the same month in the previous year. Consequently, any regular seasonal fluctuation are already embedded in the value for the previous month. Hence such seasonal fluctuations will be implicitly present in the final number of tourist arrivals for the current month. In contrast, if the change over the previous month is used, which has been the approach in other studies, any periodic fluctuations will have to be explicitly calculated by the model.

### III. NEURAL NETWORK ARCHITECTURE AND TRAINING

The neural network model developed in this study (Figure 1) is based on Focused Tapped Delay Line Neural Network (FTDNN) \([9]\) which relies on the assumption that the time series depend on explanatory variables and previous values of the dependent variable from a finite and fixed number of time steps in the past. The assumption taken in the current model was that the number of tourist arrivals depends primarily on the values of the explanatory factors from the last twelve months. Having in mind the seasonal character of tourism, such an assumption is justified.

![Fig. 1. FTDNN architecture modeling the effect of political instability on tourism demand.](image)
The available normalized data of 19 years was split into test set containing data for the years 1980, 1990, 1995, 1996 and 1997, and training/validation sets containing the data for the rest of the years. Such choice of training/validation and test data, allows examination of the model for the tourist arrivals at the beginning, the middle and the end of the observed period. Structural breaks in the data were present in both training and test data. In other words, the performance of the model could be examined throughout the period of available data, as well as in extreme conditions of structural breaks.

The model was trained using error back-propagation minimizing the standard sum of squares output error, in order to allow for the full set of experiments presented in this paper. The results reported in the next section however present relative error measures in order to allow comparison of results with other studies, almost all of which report relative errors. A separate network was trained for each of the countries being modelled (i.e. Cyprus, Greece, Israel, Turkey).

IV. EXPERIMENTS

The model performance reported here is based on the mean absolute percentage error (MAPE) and normalised correlation coefficient ($r$).

To calculate MAPE the following formula was used:

$$ MAPE = \frac{\sum_{i=1}^{n} |X_i - Y_i|}{n} \times 100\% $$

where $X_i$ and $Y_i$ represent the estimated and actual tourist arrivals for $i = 1, \ldots, 60$ from the 60 months test data.

The normalised correlation coefficient $r$ measures the closeness of the observed and estimated arrivals

The formula that was used to calculate $r$ is as follows:

$$ r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2} \cdot \sqrt{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}} $$

where $X_i$ and $Y_i$ represent the estimated and actual tourist arrivals for $i = 1, \ldots, 60$ from the 60 months test data.

Figures 2-5 present the results of the model estimating the number of tourist arrivals for the countries of Cyprus, Greece, Israel and Turkey respectively. The graphs show that the estimated neural network model values follow quite closely the pattern of actual arrivals for the country.

Comparing the MAPE figures for all four countries shows that the Greece and Israel have the lowest MAPE, 8.69% and 8.39% respectively, while the Turkey and Cyprus have 10.97% and 11.63% respectively. The low MAPE indicates that the deviations between the discrepancies among the predicted values derived by the neural network and the actual values are very small. According to Law and Au [2]...
for a MAPE within a 15% discrepancy range, the neural network succeeds in achieving approximately 80% of the output in the acceptable range. Furthermore, the normalised correlation of the coefficient between the predicted and actual values ($r$) is very high for all three countries with values of almost 1. Greece and Turkey have the highest value of $r$, 0.9955, with similarly high results for Israel and Cyprus of 0.9947 and 0.9950 respectively. A high value of $r$ is an indicator of the close relationship between the estimated results and the actual tourism data.

The ‘Noise’ results in each of the figures presents the output of the neural network if the political instability factors are removed from the input, that is the network is trained with the political instability factors, but later tested without them (i.e. inputs are set to 0). While some general degradation of performance is expected across all models, what is interesting is the comparative result between the countries. It can be seen that for some countries, such as Israel and Turkey, this can have a significant effect on the
accuracy of the estimated values, where for others, Greece in particular, the effect is relatively small.

V. EVALUATING THE IMPORTANCE OF ECONOMICAL AND POLITICAL FACTORS

Following the results presented above, the importance of each of the factors from the neural network’s input, economic as well as political instability ones, were evaluated for their relative importance in estimating the tourism demand in each of the countries. The four networks trained with the full set of input features were evaluated in separate tests where one of the input dimensions was set to 0. The relative importance of a factor was calculated as proportional to the neural network’s output error during tests with the data of that factor being ignored. The output error was calculated over the entire dataset (i.e. training, validation and test data). When a particular input factor is removed, a higher output error will indicate that this factor is more significant in the performance of the model, i.e. higher importance/effect on tourism demand, whereas a lower error would indicate relatively lesser degree of significance.

The results presented in Figures 6-9 show the relative importance of the economic and political instability factors in estimating the tourism demand for each of the four countries.

The removal of political instability factors from the model of Israel produces the highest output error compared with the other countries, clearly indicating that the factors have a significant influence on the tourism demand for this country. Similar are the results for Turkey. These findings are not surprising since both Israel and Turkey have both suffered from prolonged of internal conflict and instability during the period which is being modelled here (about 45% of all political instability events, which are reported in POLINST,
happened in Israel).

The results for the other two countries, Cyprus and Greece, show a more evenly distributed significance of the economic and political instability factors on the tourism demand.

VI. MODELING THE TIME-LAG OF POLITICAL INSTABILITY EVENTS

The most representative case of influence of the political instability from the previous section, i.e. Israel, was considered for the final experiment, where the time lag of the effect of political instability events was examined. Similarly to the previous set of experiments, in a sequence of tests, the data of political instability for each of the preceding twelve months was suppressed from the input of the network. The resulted output error for each of the twelve months was recorded and compared (Figure 10). As the results show, the neural network estimates that the most significant effects of the political instability event appear about 2 month later.

The results are compatible with those found by Enders and Sandler in their study of terrorism and tourism in Spain [10]. Using VAR analysis they attempted to estimate the impact of terrorism on tourism in Spain during the period from 1970 to 1980. Their findings suggested that after a 'typical' terrorist incident tourism to Spain began to decline at the beginning of the third month.

VII. CONCLUSION

The results of the model presented here, confirmed the current opinion on the strong influence that events of political instability can have on the tourism industry. The series of experiment revealed further details on the inter-relationship between the political instability factors and the number of tourist arrivals, as well as the relative importance between economic and political instability factors for different countries.

Furthermore, within a single neural network model we were able to achieve several different types of results on the relation between political instability and tourism, namely, we were able to estimate the tourism demand based on a combination of political instability and traditional economic factors; we were also able to show the relative importance of political instability to tourism demand and the relative differences of its effects in different countries; we were also able to assess the relative significance of the political instability and economic factors on tourism demand; and lastly we were able to confirm similar results (from other studies) on the time lag between a political instability event and its effect on tourism demand.
This study clearly demonstrates that the neural network model developed here represents an effective approach towards modelling tourism demand and offers a computational paradigm for studies in the prediction of cause and effect relationships tourism economics and management.

REFERENCES


