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COMBINATION FORECASTS OF INTERNATIONAL DEMAND FOR TOURISM IN TUNISIA

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Abstract

This paper aims to model and predict international tourism demand in Tunisia using modern econometric techniques by testing the hypothesis that the forecast combination method improves the predictive accuracy of individual models.

Empirical study is conducted using monthly data of six tourism source markets for Tunisia over the period 1997-2009. We use two forecast errors measures, MAPE and RMSPE, to assess alternative individual forecasting models and combination techniques. Our results provide robust evidence suggesting that combination forecasts, in general, outperform the individual forecasts. The combination method allows reducing the risk of total failure of the prediction by improving the accuracy of the worse predictions. The empirical results of combination techniques show some disparities across the forecast horizon.

Keywords: Tourism demand, Forecast combination, Individual models, Predictive accuracy.

JEL Classifications: C32, C53, L83.

1. Introduction

The forecast is an important and inevitable task for all industries and several studies explain the need for accurate forecasts of tourism demand (Song and Witt, 2006; Shen et al. 2008). In fact, accurate forecasts allow planners and policy makers in the tourism sector to minimize the risks associated with the overestimation of tourism demand such as oversupply of infrastructure, inefficient use of resources, low incomes of investment and unsold flights, but also the risks of an underestimation of the demand, e.g., congestion, poor service supply and the loss of market share in favor of other destinations.

In practice, a decision maker may have to choose among several methods of forecast. However, each method has its own advantages and disadvantages, and no criterion can be used to determine the appropriate method of prediction when a particular exercise of forecasting tourism demand is implemented. In fact, once the individual forecasts established, the typical reaction is to try to discover what is the best prediction; then it is accepted and used, the others are discarded. Nevertheless, this procedure is not prudent since the discarded forecasts may contain some useful independent information. The combination forecast method was introduced

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by Bates and Granger (1969) as a solution to this problem and has shown improvement in predictive accuracy. Since then, a large number of studies relating to the combination of forecasts have been developed such as Dickinson (1973, 1975), Newbold and Granger (1974), Granger and Ramanathan (1984) and Min and Zellner (1993). This approach aims to achieve more stable and accurate forecasts and that by combining the advantages of different individual models of prediction.

Empirical results from the general literature of forecast (Chan et al., 1999, Diebold and Pauly, 1990) show that the combination of forecasts provided by different models can significantly improve predictive performance relative to individual forecasts, but also allows to avoid the difficulties and risks associated with model selection, and subsequently to reduce the risk of forecasting total failure.

In the tourism context, there has been some empirical works concerned with the forecasts combination method, such as the study conducted by Fritz et al. (1984), who concluded that this approach improves the accuracy of prediction of air visitors to the State of Florida. However, the empirical results are doubtful since in this study, the authors considered a traditional econometric model that does not take the non-stationarity of time series into account. Furthermore, Oh and Morzuch (2005) revealed that the combined forecasts, using the simple average technique, of four competing time series models always outperform the poorest individual forecasts, and sometimes even perform better than the best individual model. More recently, Wong et al (2007) drew an analogous conclusion that combined forecasts can generally outperform the worst individual forecasts, thus risk of total forecast failure could be reduced through forecast combination. Shen et al. (2011) and Shen et al. (2008) have confirmed these findings and have shown additionally that the relative performance of the combination method varies according to the tourist flows by origin-destination, depending on the technique of combination used and with the forecast horizon.

On another hand, some recent empirical studies have treated the modeling and forecasting of tourism demand, such as Assaf et al. (2011) and Athanasopoulos and de Silva (2012). The first study focused on the persistence in the international monthly tourist arrivals to Australia by employing a diversity of methods based on fractional integration and seasonal autoregressions. The authors proposed also to assess the forecasting performance of several competing models. While in the second article, the authors have evaluated the forecasting accuracy of a new set of multivariate stochastic models that capture time-varying seasonality within the vector innovations structural time-series (VISTS) context, compared to the forecasting accuracy of univariate approaches using international tourist arrivals from 11 origin countries to Australia and New Zealand. Other works have investigated the impact of an appropriate treatment of seasonality on the predictive performance of the model such as Kulendren and Wong (2005), Shen et al (2009) and Gasmi (2013).

This study provides more robust empirical evidence on the usefulness of combinations forecast. We examine whether this method could improve the overall forecasting accuracy of individual models in the tourism context. This research complements the existing literature by providing some contributions. First, we use a varied array of forecast combination techniques on a wide Tunisian tourism dataset. Second, we test whether the performance of these techniques is still valid in the particular case of regional data. Indeed, we use aggregate data by grouping origin countries in six major source tourists markets to Tunisia. Finally, according to the supply-induced demand theory, we consider tourism supply variables as determinants of tourism demand. Our empirical investigation provides to planners essential information about the strategy to follow in order to increase tourism flows in the destination and preserve its markets share.

The paper is organized as follows: the second section will be devoted to a brief presentation of individual models of forecast that will be used in this work to forecast the international tourism demand in Tunisia. In this section, we will also present the combination forecasts method and its different techniques. Measures of predictive accuracy will be the object of the third section. Sections 4 and 5 will be devoted respectively to the data description and the empirical results, to finally conclude.

2. Forecasting Methods

2.1 Individual models

In this article, we focus on the analysis of Box and Jenkins (1976) through the seasonal ARIMA or SARIMA model. We are also interested in the forecasts provided by the error-correction (ECM) and vector autoregressive (VAR) models. The choice of these models is explained by the fact that they have been widely and successfully used in forecasting international tourism demand (Li et al., 2005, Wong et al. 2007, Song et al. 2003; Kulendran and King, 1997, Shen et al., 2009, Shen et al., 2011, etc.).

As monthly data are employed, the time series are likely to display seasonality. The HEGY test established by Hylleberg, Engle, Granger and Yoo (1990) is thus implemented to test for the presence of seasonal and non-seasonal unit roots. Two types of seasonality are defined: stochastic and deterministic seasonality. We consider here the seasonality as a stochastic component since the seasonal pattern of the data series examined in this study evolves over time. In this case, seasonal differencing is required.

2.1.1 SARIMA model

Box and Jenkins (1976) show that the study of time series using ARIMA process could be applied to many economic areas for forecasting grounds. In fact, the time series analysis methods are to search in the history of the variable the regularities that may help to predict its future values. SARIMA model can be seen as a generalization of ARIMA models, containing a seasonal part. This model has proven to be efficient in modeling and forecasting monthly and quarterly times series.

A collection of SARIMA models with different orders of p, q, P, Q are estimated first, and one model is selected using information criteria as the Akaike Information Criterion (AIC) and Schwarz criterion (SC). The orders of p, q, P and Q are chosen from 0 to 2, according to Pankratz (1991), who suggests that in practice, all the orders (p, d, q, P, D, Q) tend to be small, frequently no more than 1 or 2 for SARIMA processes.

2.1.2 Vector Autoregressive model (VAR)

The VAR model is a system of equations proposed by Sims (1980). It is a method that treats all variables as endogenous, with the exception of deterministic variables (constant, trend, dummy variables). This method has been widely used in modeling and forecasting macroeconomic and tourism activities. In fact, several studies (Song and Witt, 2006, Wong et al., 2007, Shen et al., 2011) have successfully applied this technique to forecast tourism demand.

The estimation of a VAR model requires seasonally adjusted and stationary variables. For this, we apply to each of the variables considered in the study, the seasonal and non-seasonal differentiation filters suggested by the HEGY test. The VAR model estimation requires the determination of the lag order p. To determine the optimal number of lags for a VAR(p), several methods can be used . A typical procedure is to estimate VAR models for all orders p ranging from 0 to a certain order k arbitrarily fixed.

Selecting the appropriate model is based on information criteria (AIC and SC). For each tourist market, the lag order retained is as follows:

- VAR(7) for the Western European market
- VAR(6) for the North African market;
- VAR(7) for the market in Central and Eastern Europe ;
- VAR(6) for the Scandinavian market ;
- VAR(4) for the Middle East market ;
- VAR(5) for the North American market.

All VAR models are estimated by the maximum likelihood method, and their validity is verified using the Portmanteau test which the null hypothesis assumes that there is no residual autocorrelations up to lag k.

2.1.3 Error Correction Model (ECM)

We propose in this paper to apply the two-step procedure of Engle and Granger (1987). After checking that all variables are integrated of the same order, the first step of this procedure is to estimate by OLS method the long-term relationship (1) below between the dependent variable and the explanatory variables and to test the stationarity of the regression residuals using the ADF test. If the residuals are stationary, then the long-term regression is a cointegration relationship.

$$y_t = \alpha + \sum_{i=1}^{n} \beta_i x_{it} + \varepsilon_t \qquad \text{... (1)}$$

In the second step, the cointegration relationship is transformed into an error-correction process that takes the following form:

$$\Delta y_t = \sum_{i=1}^{n} \sum_{j=1}^{p} \gamma_i \Delta x_{it-j} + c(y_{t-1} - \alpha - \sum_{i=1}^{n} \beta_i x_{it-1}) + u_t \qquad \text{... (2)}$$

Equation (2) represents the short-run relationship between the variables.

2.2 The combination methods

Many combination techniques have been developed in the literature. In this study, we use three combination techniques: the simple average method, the variance-covariance method and the Granger and Ramanathan (1984) regression method. Our choice is justified by the fact that these approaches have been widely used in the general literature inherent to forecasting and most other methods (e.g., the discounted mean square forecast error method, the shrinkage method and the time-varying-parameter combination method) are developed from or modified versions of these methods.

2.2.1 Simple average combination method

The simple average combination method calculates combined forecasts by taking the arithmetic average of individual forecasts. Empirical studies (Palm and Zellner, 1992, Makridakis and Winkler, 1983) show that this method can generate accurate forecasts in many cases, and sometimes even more robust than other combination techniques.

2.2.2 Variance-covariance method (Bates and Granger, 1969)

Despite the efficiency of the Simple average combination technique in improving the predictive accuracy, many researchers have preferred assigning greater weight to all of forecasts that seem to contain the weakest errors. We distinguish thus weighted average combination methods which calculate weights based on the past performance of each individual forecast model. Among these methods is cited mainly the variance-covariance method in which the weights are determined by a covariance matrix where individual forecast accuracy is incorporated into the variances, while the dependence between the individual forecasts is interpreted by the covariance.

2.2.3 Regression method (Granger and Ramanathan, 1984)

Granger and Ramanathan (1984) suggest a linear combination method where the weights are estimated by OLS. Common practice at the level of combination method is to require that the sum of the weights assigned to each of the initial forecasts is equal to unity.

The authors show that the best method is to add a constant in the regression and not to restrict the amount of weights to the unit. In addition, they reveal that the individual forecasts will not be biased from the moment that any bias will be corrected by the constant term.

3. Accuracy Measures

The evaluation of the predictive accuracy is naturally based on ex-post forecasts. In this regard, various measures of predictive accuracy or more precisely of the magnitude of forecast errors exist. Before exposing them, it is first necessary to examine the potential sources of forecast errors.

3.1 Sources of errors

Despite the large number of studies assessing the economic predictions, knowledge about the sources of forecast errors is very limited. In fact, in the presentation of measures of the magnitude of forecast errors, most studies do not examine the causes of errors or bias, nor do they try to determine whether the errors are significant relative to the best forecast that could be performed (Stekler, 2007). In contrast, there are a number of problems inherent to the interaction between models and data. Wallis (1986) shows that the prediction accuracy is affected by the inability to determine the exact state of the economy at the time the forecast is performed. This occurs because, at any moment, the available data on the variables of interest are of different sizes. In addition to the problems associated with the need to use data to make preliminary forecasts, there are problems related to data collection and to the sample period chosen to estimate the model.

3.2 Measures of errors

The comparison of the forecasting performance of different used methods requires the choice of a particular measure of predictive accuracy or performance. Several studies (Song et al., 2003, Li et al., 2005, Wong et al., 2007) show that the two most frequently used measures are the MAPE (Mean Absolute Percentage Error) and the RMSPE (Root Mean Square Percentage Error). Shen et al. (2011) conclude that these two measures result in highly consistent individual and combination forecast performance evaluations.

Besides, the MAPE and the RMSPE have the merits to be expressed without units, so that they facilitate comparisons between different data sets.

In addition, Witt and Witt (1992) suggest that the MAPE is the most appropriate error measure for the evaluation of the forecasting performance of tourism models. These two measures are calculated respectively as follows:

$$\mathrm{MAPE} = \frac{\sum_{t=1}^{h} |e_t| / y_t}{h} \qquad \text{... (3)}$$

$$\mathrm{RMSPE} = \sqrt{\frac{\sum_{t=1}^{h} (e_t / y_t)^2}{h}} \qquad \text{... (4)}$$

Where e_t is the prediction error, y_t is the current value of the forecast variable, and h is the length of the forecasting horizon. The best forecasting method corresponds to the weakest MAPE and RMSPE.

4. Data

In this work, we focus on six source markets of tourists to Tunisia, namely the West European market, the Central and East Europe market, the Scandinavian market, the Maghreb market, the Middle East market and the North American market. Table 3 in the appendix shows the countries included in the sample by region. The study is conducted on monthly Tunisian data covering the period from January 1997 to December 2009. For the estimation, we use the data between January 1997 and December 2008, the twelve remaining observations, i.e., from January 2009 until December 2009 will be used for forecasting and the evaluation of the predictive performance of the model to be estimated from previous observations.

Travel and tourism data are provided by the Tunisian National Tourism Office in the form of an annual report on tourism activity in Tunisia "The Tunisian Tourism in Figures" and by the Civil Aviation and Airports Office, while macroeconomic data are obtained from the statistical base “IFS” of the International Monetary Fund (IMF).

Through several studies, such as Shen et al. (2011), Shen et al. (2009), Wong et al. (2007), Kulendran and King (1997), Martin and Witt (1989), Witt and Witt (1995), etc.., we note that the most frequently used variables are tourist arrivals as the dependent variable and for the explanatory variables, we usually consider the price of tourism, the consumer income, seasonal dummy variables, one-off events dummies (e.g., the events of September 11, 2001), linear trends as well as the tourism supply in the case of the supply-induced demand theory (Ouerfelli, 2008, Dupont, 2006).

Given this, the tourism demand function in our study takes the following general form:

$T_{it} = (Y_{it}, OP_{it}, SP_{it}, OF_t, \text{dummy variables})$

Where:

- T_{it}: is the international tourism demand for the Tunisian destination measured by the monthly tourist arrivals from six origin regions;

- Y_{it}: denotes the tourist income in the origin country measured by the industrial production index (IPI);

- OP_{it}: represents the relative price of tourism in the destination country (the own price) calculated by dividing the price of the destination (Tunisia), measured by the consumer prices index (CPI_{TN}), by the CPI in the origin country (CPI_{it}) and adjusted by the appropriate exchange rates (EX_{TN}, EX_i) as follows:

$$OP_{it} = \frac{CPI_{TN} / EX_{TN}}{CPI_i / EX_i} \quad \text{... (5)}$$

- SP_{it}: defines the relative price of substitution in Morocco, the main direct competitor of Tunisia. It is measured by dividing the consumer prices index of the rival destination by the consumer prices index of country *i* adjusted by the corresponding exchange rates:

$$SP_{it} = \frac{CPI_{Morocco} / EX_{Morocco}}{CPI_i / EX_i} \quad \text{... (6)}$$

- OF_t: is the tourism supply. Favorable nature and climate as well as a rich cultural product do not guarantee systematically the choice of a destination. To ensure customer loyalty, the tourism stakeholders should provide adequate infrastructure and show great hospitality. The package offered to a tourist visiting Tunisia includes mainly the stay in a hotel and the air transport. The accommodation capacity is an important component of tourism supply. In fact, it can affect potential demand by reflecting the quality of the product and by giving a brand image of the destination. As a proxy of the hotel capacity, we use the monthly average capacity put into operation, which is equal to the total number of beds divided by the total number of hotels.

The air supply constitutes also another important component of the tourism offer. It is measured by the number of flights offered by airline companies. The flights programming is performed by airlines in advance and should be addressed to the general direction of the Civil Aviation for review and approval.

For the industrial production index (IPI), the consumer price index (CPI) and the exchange rates variables, we considered those of the most representative country of each group, i.e., the most tourists' flows transmitter country:

- For the West European market, we took the variables relative to France;
- For the market of Central and East Europe, we took Poland as a representative country of this group;
- For Scandinavian countries: Sweden;
- For the Maghreb market: Algeria;
- For the Middle East: Saudi Arabia;
- For the North American market: The United States.

Finally, some one-off events are taken into account in the form of dummy variables (e.g., the events of 11 September 2001 (D1); the attacks of Djerba in April 2002 (D2), the global financial and economic crisis, in October 2008 (D3)). All variables except dummy variables are transformed into logarithms and double-logarithmic models are used to explain the relationship between tourism demand and its determinants.

5. Empirical Results

5.1 The forecasting performance of the individual models

Estimated SARIMA, VAR and EC models can provide forecasts with filtered data (stationary and deseasonalized series). However, the computation of forecast errors measures (MAPE and RMSPE) for assessing the predictive accuracy must be based on the raw data. Re-processing by removing seasonal and non-seasonal differentiation filters of these filtered forecasts is then required.

The forecast results are presented in table 1 relating to the six tourism markets examined in the study. We consider five forecast horizons: the one-month horizon (*h*1), the two-month horizon (*h*2), the three-month horizon (*h*3), the six-month horizon (*h*6) and the twelve-month horizon (*h*12).

To ensure conformity with all previous tourism forecasting studies, our comparison of accuracy is based on frequently used errors measurements: MAPE and RMSPE. These measures lead to very convergent assessments of the performance of individual forecasts and of forecast combinations.

On the entire out-of-sample period, that is to say, at the horizon of twelve months, we find that the time series model (SARIMA) is superior to the two other models in forecasting tourist arrivals in Tunisia coming from all origin regions, with the exception of the Middle East where the seasonal ARIMA model is ranked second. The error correction model (ECM) is ranked third in the case of West Europe, the Arab Maghreb and the Middle East, and is ranked second for the rest of the regions. In contrast, the VAR model is ranked second in the prediction of West European and Maghrebian arrivals, third in forecasting Central and East-European, Scandinavian and North American arrivals and first in forecasting arrivals from Middle East.

At the one-month horizon, the most accurate forecasts are generated by the SARIMA model, for all origin regions. ECM and VAR model are ranked second and third respectively in predicting tourist arrivals from the West Europe, the Arab Maghreb, the Central and East Europe and the Middle East. While in the case of the Scandinavian countries and North America, the VAR model is ranked third and the ECM is ranked second.

Table 1. Evaluation of individual forecasts

Forecast Error Measure	Horizon	West Europe			Arab Maghreb			Central and East Europe		
		S	**V**	**E**	**S**	**V**	**E**	**S**	**V**	**E**
MAPE	***h*1**	0.02*	0.03	0.09	0.05*	0.07	0.11	0.08*	8.07	9.49
	***h*2**	0.06	0.08	0.05*	0.10	0.05*	0.18	0.05*	2.12	3.74
	***h*3**	0.03*	0.12	0.20	0.16	0.13*	0.15	0.19*	0.77	0.69
	***h*6**	0.03*	0.06	0.37	0.20	0.17*	0.20	0.25*	40.05	38.6
	***h*12**	0.06*	0.13	0.54	0.13*	0.15	0.27	0.27*	10.08	9.93
RMSPE	***h*1**	0.02*	0.03	0.09	0.05*	0.07	0.11	0.08*	8.07	9.49
	***h*2**	0.05*	0.10	0.06	0.13	0.06*	0.22	0.07*	2.84	5.11
	***h*3**	0.04*	0.13	0.22	0.18	0.19	0.17*	0.21*	0.80	0.76
	***h*6**	0.04*	0.08	0.42	0.24	0.20*	0.23	0.29*	91.35	87.1
	***h*12**	0.07*	0.16	0.65	0.17*	0.18	0.32	0.32*	20.04	18.7
Forecast Error Measure	**Horizon**	**Scandinavian countries**			**Middle East**			**North America**		
		S	**V**	**E**	**S**	**V**	**E**	**S**	**V**	**E**
MAPE	***h*1**	0.24*	0.46	0.46	0.06*	0.44	0.46	0.04*	0.17	0.07
	***h*2**	0.33	0.44	0.29*	0.16*	0.17	0.29	0.03*	0.18	0.05
	***h*3**	0.27	0.34	0.23*	0.27	0.30	0.23*	0.09*	0.13	0.10
	***h*6**	0.25*	0.38	0.40	0.28	0.16*	0.40	0.10*	0.13	0.18
	***h*12**	0.25*	0.64	0.36	0.18	0.16*	0.36	0.07*	0.41	0.36
RMSPE	***h*1**	0.24*	0.46	0.46	0.06*	0.44	0.46	0.04*	0.17	0.07
	***h*2**	0.43	0.45	0.32*	0.18*	0.19	0.32	0.03*	0.18	0.06
	***h*3**	0.39	0.36	0.27*	0.38	0.33	0.27*	0.10*	0.16	0.11
	***h*6**	0.29*	0.44	0.47	0.38	0.20*	0.47	0.12*	0.16	0.19
	***h*12**	0.29*	0.68	0.42	0.28	0.20*	0.42	0.09*	0.42	0.38

S, V, E denotes SARIMA model, VAR model and ECM model, respectively
** designates the best individual forecast.*

At the two-month horizon, the SARIMA model is ranked first in forecasting East-European, Middle East and North American arrivals, while it is ranked second for forecasting tourist arrivals from West Europe, Arab Maghreb and Scandinavia. VAR model predictions are the most accurate in the case of the Arab Maghreb countries. However, they are ranked second in forecasting arrivals coming from Central and East Europe and Middle East, and third in the prediction of arrivals from West Europe, Scandinavia and North America. As for the ECM, it provides the best forecasts in the case of West Europe and the Scandinavian countries, and the least accurate predictions for the case of the Arab Maghreb, East Europe and the Middle East. This model is ranked second for North America.

At the three-month horizon, the best forecasts are derived from the SARIMA model in the case of West Europe, Central and East Europe and North America, from the VAR model in the case of the Arab Maghreb and from the ECM in the cases of the Scandinavian countries and the Middle East. In contrast, the least accurate forecasts are provided by the VAR model in the case of East Europe, Scandinavian countries, the Middle East and North America. While SARIMA model and ECM provide respectively the less accurate forecasts in the case of the Arab Maghreb and the case of West Europe.

At the six-month horizon, the SARIMA model generates the best forecasts in the case of West Europe, East Europe, the Scandinavian countries and North America. In the contrary, it provides the less accurate predictions in the case of the Arab Maghreb. The VAR model meanwhile is ranked first in forecasting Arab Maghreb and Middle East arrivals, second in the prediction of arrivals from West Europe, Scandinavia and North America and third in forecasting Central and East European arrivals. Finally, the ECM is ranked first in forecasting Maghrebian and East European arrivals. However, this model generates the less accurate forecasts in the case of West Europe, Scandinavian countries, the Middle East and North America.

It should also be noted that in the case of Central and East Europe, the forecasts of ECM and VAR model are very poor since the MAPE and RMSPE values exceed 1. Thus, the level of performance reached by the individual forecasting models varies by origin region and depending on the forecast horizon. The combination of forecasts may therefore be a suitable alternative. Consequently, these results suggest that no single forecasting method can generate the best forecasts in all situations. This is consistent with the results of Wong et al. (2007) and Shen et al. (2011).

5.2 The forecasting performance of the combination methods

The general economic literature, unrelated to tourism, shows that the combination of forecasts can improve forecast accuracy and reduce the risk of forecast total failure. The purpose of this study is to test this proposal in the context of tourism demand, and by examining the efficiency of different techniques of combining forecasts relative to the predictive performance of individual models used in this work. Results are given in table 2 below.

Figures in bold indicate that the combination forecasting is better than the most accurate individual forecast included in the combination. Normal numbers indicate that the forecast combination is better than the least accurate individual forecast included in the combination.

The results suggest that the simple average method is the least efficient compared to the two other techniques of combining forecasts. Although this technique can improve the accuracy of prediction results of the individual method of the least accurate forecast included in the combination, but it is rarely better than the most accurate individual forecast included in the combination.

This finding is valid for all the origin regions and all forecast horizons. The poor performance of the simple average technique can be explained by the fact that it gives equal weights to the different individual forecasts without making the distinction between a good and a bad forecast. In contrast, the variance-covariance technique lends greater weight to the most accurate individual forecasts. When compared to the simple average method, we can conclude that it is more efficient since it shows forecast errors (MAPE and RMSPE) lower than the simple average technique. Moreover, we note that on the entire out-of-sample period (i.e., at the horizon of twelve months), the variance-covariance method is highly efficient in forecasting tourist arrivals from West Europe, the Arab Maghreb, the Middle East and North America, where almost all combined forecasts are better than the most accurate forecasts. For Central and East Europe and the Scandinavian countries, the performance of this technique is limited to the reduction of the failure of the least accurate individual forecast contained in the combination.

Finally, the comparison of the three combination techniques allows the detection of the superiority of Granger and Ramanathan (1984) regression method relative to the simple average technique and the variance-covariance technique. In fact, this technique admits the weakest prediction errors. In addition, it improves the accuracy of the predictive results of all individual models, including the individual model that generates the best forecasts.

It also enables, in some cases where the MAPE and RMSPE exceed 1, to avoid total failure of the forecast as in the case of the Central and East Europe, or at least to reduce the risk of failure.

Table 2. Evaluation of Combinations Forecasts

Forecast Error Measure	Horizon	West Europe											
		SV			SE			VE			SVE		
		SA	VC	GR	SA	VC	GR	SA	VC	GR	SA	VC	GR
MAPE	***h*1**	0.02	0.02	**0.00**	0.06	0.03	**0.00**	0.06	0.03	**0.00**	0.05	0.03	**0.00**
	***h*2**	0.05	0.05	**0.00**	0.05	0.05	**0.00**	0.05	0.05	**0.00**	0.05	0.05	**0.00**
	***h*3**	0.08	0.04	**0.00**	0.10	0.03	**0.00**	0.13	**0.10**	**0.03**	0.09	0.04	**0.00**
	***h*6**	0.04	0.03	**0.01**	0.19	**0.03**	**0.01**	0.17	**0.06**	**0.01**	0.11	0.03	**0.01**
	***h*12**	0.06	**0.05**	**0.04**	0.26	**0.06**	**0.05**	0.27	**0.11**	**0.09**	0.17	**0.05**	**0.04**
RMSPE	***h*1**	0.02	0.02	**0.00**	0.06	0.03	**0.00**	0.06	0.03	**0.00**	0.05	0.03	**0.00**
	***h*2**	0.07	0.05	**0.00**	0.05	0.05	**0.00**	0.06	**0.05**	**0.00**	0.06	**0.05**	**0.00**
	***h*3**	0.08	0.04	**0.00**	0.10	0.04	**0.00**	0.14	0.13	**0.04**	0.10	**0.04**	**0.00**
	***h*6**	0.05	0.04	**0.01**	0.22	0.04	**0.01**	0.20	0.07	**0.01**	0.14	0.04	**0.01**
	***h*12**	0.08	**0.06**	**0.06**	0.32	**0.07**	**0.05**	0.30	**0.14**	**0.11**	0.19	**0.06**	**0.05**
Forecast Error Measure	**Horizon**	**Central and East Europe**											
		SV			**SE**			**VE**			**SVE**		
		SA	**VC**	**GR**	**SA**	**VC**	**GR**	**SA**	**VC**	**GR**	**SA**	**VC**	**GR**
MAPE	***h*1**	3.99	**0.08**	**0.00**	4.71	**0.08**	**0.00**	8.78	8.66	**0.00**	5.83	**0.08**	**0.00**
	***h*2**	1.03	**0.05**	**0.00**	1.89	**0.05**	**0.00**	2.81	2.44	**0.00**	1.89	**0.05**	**0.00**
	***h*3**	0.29	**0.15**	**0.14**	0.25	**0.15**	0.22	0.73	0.73	**0.00**	0.42	**0.11**	**0.00**
	***h*6**	20.09	0.28	**0.20**	19.36	0.29	**0.20**	39.34	39.30	**2.37**	26.26	0.31	**0.18**
	***h*12**	5.07	0.43	**0.14**	4.97	0.44	**0.14**	10.01	10.00	**2.45**	6.67	0.59	**0.17**
RMSPE	***h*1**	3.99	**0.08**	**0.00**	4.71	**0.08**	**0.00**	8.78	8.66	**0.00**	5.83	**0.08**	**0.00**
	***h*2**	1.41	**0.07**	**0.00**	2.55	**0.07**	**0.00**	3.97	3.37	**0.00**	2.64	**0.07**	**0.00**
	***h*3**	0.30	**0.16**	**0.00**	0.28	**0.16**	**0.03**	0.78	0.78	**0.00**	0.45	**0.12**	**0.00**
	***h*6**	45.77	0.34	**0.26**	43.60	0.34	**0.26**	89.18	89.05	**4.52**	59.51	0.39	0.29
	***h*12**	10.06	0.53	**0.17**	9.40	0.53	**0.17**	19.33	19.30	**3.81**	12.92	0.82	**0.22**
Forecast Error Measure	**Horizon**	**Middle East**											
		SV			**SE**			**VE**			**SVE**		
		SA	**VC**	**GR**	**SA**	**VC**	**GR**	**SA**	**VC**	**GR**	**SA**	**VC**	**GR**
MAPE	***h*1**	0.25	0.06	**0.00**	0.26	0.06	**0.00**	0.45	0.45	**0.00**	0.32	0.07	**0.00**
	***h*2**	**0.05**	**0.05**	**0.00**	**0.14**	**0.16**	**0.00**	0.23	0.20	**0.00**	**0.13**	**0.08**	**0.00**
	***h*3**	**0.23**	**0.23**	**0.00**	**0.20**	**0.20**	**0.19**	0.26	0.26	**0.00**	0.23	0.23	**0.00**
	***h*6**	0.20	0.20	0.19	0.29	**0.25**	**0.21**	0.27	0.22	**0.15**	0.24	0.20	0.20
	***h*12**	**0.14**	**0.14**	**0.12**	0.19	0.18	**0.15**	0.24	0.19	0.17	0.16	**0.14**	**0.14**
RMSPE	***h*1**	0.25	0.06	**0.00**	0.26	0.06	**0.00**	0.45	0.45	**0.00**	0.32	0.07	**0.00**
	***h*2**	**0.07**	**0.07**	**0.00**	0.18	**0.16**	**0.00**	0.23	0.20	**0.00**	**0.15**	**0.10**	**0.00**
	***h*3**	**0.28**	**0.28**	**0.00**	**0.24**	**0.24**	**0.23**	0.27	**0.27**	**0.00**	**0.24**	**0.24**	**0.00**
	***h*6**	0.23	0.23	0.22	**0.30**	**0.30**	**0.25**	0.31	0.25	**0.19**	0.25	0.23	0.22
	***h*12**	**0.17**	**0.16**	**0.15**	**0.22**	**0.21**	**0.18**	0.29	0.23	**0.19**	**0.20**	**0.16**	**0.16**

Table 2. Evaluation of Combinations Forecasts (Contd.)

Forecast Error Measure	Horizon	Arab Maghreb											
		SV			SE			VE			SVE		
		SA	VC	GR	SA	VC	GR	SA	VC	GR	SA	VC	GR
MAPE	*h*1	0.06	0.06	**0.00**	0.08	0.02	**0.00**	0.09	0.08	**0.00**	0.08	0.06	**0.00**
	*h*2	0.05	**0.04**	**0.00**	0.13	0.11	**0.00**	0.10	**0.04**	**0.00**	0.10	**0.05**	**0.00**
	*h*3	0.14	0.14	**0.07**	**0.09**	**0.08**	**0.07**	0.07	**0.07**	**0.05**	**0.10**	**0.09**	**0.00**
	*h*6	**0.17**	**0.17**	**0.11**	**0.13**	**0.14**	**0.11**	**0.12**	**0.12**	**0.08**	**0.10**	**0.11**	**0.08**
	*h*12	**0.13**	**0.13**	**0.09**	0.17	0.13	**0.10**	**0.15**	**0.12**	**0.10**	**0.12**	**0.11**	**0.09**
RMSPE	*h*1	0.06	0.06	**0.00**	0.08	0.06	**0.00**	0.09	0.08	**0.00**	0.08	0.06	**0.00**
	*h*2	0.06	**0.04**	**0.00**	0.18	0.16	**0.00**	0.11	**0.05**	**0.00**	0.11	**0.05**	**0.00**
	*h*3	**0.17**	**0.17**	**0.07**	**0.14**	**0.14**	**0.08**	**0.09**	**0.10**	**0.05**	**0.12**	**0.12**	**0.00**
	*h*6	**0.20**	**0.20**	**0.14**	**0.16**	**0.16**	**0.14**	**0.14**	**0.15**	**0.10**	**0.15**	**0.14**	**0.10**
	*h*12	**0.16**	**0.16**	**0.16**	0.19	**0.16**	**0.12**	**0.18**	**0.16**	**0.12**	**0.15**	**0.14**	**0.11**
Forecast Error Measure	Horizon	Scandinavian countries											
		SV			SE			VE			SVE		
		SA	VC	GR	SA	VC	GR	SA	VC	GR	SA	VC	GR
MAPE	*h*1	**0.11**	**0.09**	**0.00**	**0.13**	**0.02**	**0.00**	**0.22**	**0.02**	**0.00**	**0.07**	**0.02**	**0.00**
	*h*2	0.38	0.39	**0.00**	0.32	0.32	**0.00**	0.38	0.35	**0.00**	0.36	0.35	**0.00**
	*h*3	0.29	0.27	**0.23**	**0.12**	**0.17**	**0.07**	**0.13**	**0.22**	**0.00**	**0.17**	**0.23**	**0.00**
	*h*6	0.28	0.27	**0.26**	**0.24**	**0.24**	**0.17**	**0.33**	**0.31**	**0.20**	0.27	0.25	**0.21**
	*h*12	0.41	0.30	**0.25**	0.32	0.25	0.31	0.38	0.39	**0.57**	0.32	0.26	0.26
RMSPE	*h*1	0.11	**0.09**	**0.00**	**0.13**	**0.02**	**0.00**	**0.22**	**0.02**	**0.00**	**0.07**	**0.02**	**0.00**
	*h*2	0.40	**0.40**	**0.00**	0.33	**0.32**	**0.00**	0.38	0.36	**0.00**	0.36	0.35	**0.00**
	*h*3	**0.34**	**0.35**	**0.29**	**0.13**	**0.27**	**0.10**	**0.17**	**0.22**	**0.00**	**0.17**	**0.27**	**0.00**
	*h*6	0.33	0.30	0.41	0.27	**0.27**	**0.22**	**0.37**	**0.34**	**0.26**	0.32	**0.29**	**0.28**
	*h*12	0.46	0.34	0.38	0.41	0.31	0.41	0.45	0.46	0.74	0.38	0.32	0.38
Forecast Error Measure	Horizon	North America											
		SV			SE			VE			SVE		
		SA	VC	GR	SA	VC	GR	SA	VC	GR	SA	VC	GR
MAPE	*h*1	0.10	0.05	**0.00**	0.05	0.05	**0.00**	0.12	0.08	**0.00**	0.09	0.05	**0.00**
	*h*2	0.08	0.03	**0.00**	0.03	0.03	**0.00**	0.06	**0.04**	**0.00**	0.04	0.03	**0.00**
	*h*3	0.11	0.10	**0.00**	**0.04**	**0.03**	**0.04**	**0.04**	**0.03**	**0.03**	**0.04**	**0.02**	**0.00**
	*h*6	**0.10**	**0.09**	**0.09**	**0.09**	**0.09**	**0.08**	0.15	0.15	**0.07**	**0.10**	**0.08**	**0.07**
	*h*12	0.19	**0.07**	**0.07**	0.17	**0.07**	**0.07**	0.38	0.38	**0.11**	0.25	**0.07**	**0.06**
RMSPE	*h*1	0.10	0.05	0.00	0.05	0.05	0.00	0.12	0.08	0.00	0.09	0.05	0.00
	*h*2	0.09	0.03	0.00	0.04	0.03	0.00	0.07	0.04	0.00	0.05	0.03	0.00
	*h*3	0.11	0.11	0.01	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.00
	*h*6	0.11	0.11	0.10	0.12	0.10	0.09	0.17	0.17	0.08	0.12	0.10	0.09
	*h*12	0.21	0.09	0.08	0.19	0.09	0.09	0.40	0.40	0.14	0.26	0.09	0.08

The ability to avoid poor forecasts would be particularly useful in cases where we do not have an idea about the performance of individual forecasting models. It would therefore be more prudent to combine forecasts.

6. Conclusion

In this research, we propose to test the hypothesis that the forecasts combination method can improve the predictive accuracy of individual models and reduce the risk of total forecasting failure. For this, we use three individual models (SARIMA model, the VAR model and the error correction model) and three methods of combining forecasts (the simple average technique, the variance-covariance technique and the regression technique). The study focuses on six origin region: West Europe, the Arab Maghreb, Central and East Europe, Scandinavian countries, the Middle East and North America.

We then use these models to predict the international tourist arrivals in Tunisia. A comparative study of the forecasting performance of the three models was conducted on the basis of the mean absolute percentage error (MAPE) and the root mean square percentage error (RMSPE) and this for different forecast horizons. The results show that the predictive performance of each of the individual models varies by origin region and with the forecast horizon, and no single model can produce the best forecasts in all situations. This conclusion is in line with those of Shen et al. (2011), Wong et al. (2007) and Song and Witt (2002). To overcome this difficult, we apply the method of forecast combination. We conclude that combinations of forecasts are not always better than the most accurate individual forecasts included in combinations.

Furthermore, the relative performance of the combination compared to individual forecasting models depends on the origin region and also on the technique of combination. Thus, we could show that the best combination technique is the regression technique which enables to obtain better forecasts than the most accurate individual prediction in all situations. The second method suggested is that of variance-covariance since it assigns a greater coefficient to the best individual forecasts, unlike the simple average technique that gives equal weights to individual forecasting models without considering their past performance. In addition, results reveal that combination method, regardless of the technique used, allows reducing the risk of total failure of the prediction by improving the accuracy of the worse predictions. This conclusion is consistent with the study of Hibon and Evgeniou (2005) who suggest that the use of an individual predictive model among a set of models, is riskier than the use of a combination of forecasting models.

Consequently, when we are in the presence of a number of econometric models and we must conduct forecasts but we are uncertain which model provides the best predictive results, combining the predictions of these models would be the best forecasting method leading to an optimal predictive accuracy.

Ultimately, this research has emphasized the efficiency of forecast combination method in improving the accuracy of individual forecasts.

Reliable and accurate forecasts allow the various actors of tourism sector and other sectors that are interrelated, including the air transport of passengers, to anticipate sufficiently earlier accommodation capacity problems and problems of airport capacity and air navigation, and to make strategic decisions about the construction of new hotels, the targeting of new tourist customers or the focusing on an advantageous clientele, and that by offering them new tourism products that can be consumed throughout the year, avoiding thus the problem of seasonality, and by enhancing the quality of supply. Other decisions may relate to the development of tourism-related infrastructure such as the future layout of airports, highways and railways, the opening of a new air line, chartering or purchasing new airplanes.

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Appendix

Table 3. Countries List

West Europe	Arab Maghreb	Central and East Europe	Scandinavian countries	Middle East	North America
France	Algeria	Serbia	Sweden	Saoudi Arabia	USA
Germany	Libya	Russia	Denmark	Syria	Canada
UK	Morocco	Czech	Norway	Iraq	
Italy	Mauritania	Slovak	Finland	Lebanon	
Switzerland		Bulgaria		Jordan	
Belgium		Hungary		Palestine	
Netherlands		Poland		Kuwait	
Austria		Romania		Sudan	
Spain		Turkey		Yemen	
Luxembourg				Qatar	
Greece				Bahrain	
Portugal				Oman	
Ireland				UAE	
Malta				Egypt	

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