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Abstract

This study utilizes both disaggregated data and macroeconomic indicators in order to examine the importance of the macroeconomic environment of origin countries for analysing destinations' tourist arrivals. In particular, it is the first study to present strong empirical evidence that both of these features in tandem provide statistically significant information of tourist arrivals in Greece. The forecasting exercises presented in our analysis show that macroeconomic indicators conducive to better forecasts are mainly origin country-specific, thus highlighting the importance of considering the apparent sharp national contrasts among origin countries when investigating domestic tourist arrivals. Given the extent of the dependency of the Greek economy on tourism income, but also, given the perishable nature of the tourist product itself, results have important implications for policy makers in Greece.

Keywords: Tourist arrivals forecasting, seasonal ARIMA, Diebold-Mariano test, disaggregated data, macroeconomic indicators.

JEL Classification: C22, C53, F19, O10.

1. Introduction

The literature has long established the importance of tourism demand forecasting. The consensus is that forecasting tourist arrivals is necessary for tourism planning, policy decision making, as well as, budgeting issues by tourism operators, especially due to the perishable nature of tourism (see, *inter alia*, Uysal and O'Leary, 1986; Law and Au, 1999; Law, 2000; Chandra and Menezes, 2001). From a macroeconomic point of view, destination's infrastructure and promotion require substantial investment and thus an estimate of the destination's future tourism demand is essential in order to safeguard a positive return on investment. From a microeconomic point of view, forecasting tourism demand is an important tool for the firms that operate in the sector, such as airlines, tour operators, hotels, etc. Finally, tourism forecasting is also necessary as a governmental tool for policy decisions which aim at accelerating economic development that is particularly crucial for countries that heavily depend on tourism income (Goh and Law, 2002; Cho, 2003; Palmer *et al.*, 2006; Song and Witt, 2006; Gounopoulos *et al.*, 2012). Given that important business decisions are based to a great extent on expectations about future market conditions, better ways of forecasting could steer both public and private decisions to more efficient and effective paths; thus, benefiting the country as a whole.

Our analysis of tourism demand puts heavy emphasis on the employment of a broader set of macroeconomic indicators of origin countries. Although there have been studies to investigate tourism demand by country of origin (see, among others, Nicolau and Mas, 2005a,b; Wang *et al.*, 2006; Rudez, 2008; Lim *et al.*, 2009; Alegre *et al.*, 2010) most of these studies have mainly focused on income of the origin country or/and on the relative price levels (*i.e.* a relatively narrow set of macroeconomic indicators of origin countries). At the same time, none of these studies has incorporated such a set of macroeconomic indicators specifically for the purposes of forecasting tourism demand. In this study, we argue that employing a variety of macroeconomic indicators might, in fact, lead to a better understanding of the forces that drive decisions in origin countries, as well as, improve the forecasting of tourism demand in destination countries. This is in line with Song *et al.* (2011) who argue in support of the development of models which incorporate a broader set of explanatory variables to explain the dynamics that drive tourism demand. Another key aspect of this study is that contrary to existing endeavours which have mainly concentrated on producing forecasts of tourism demand using a Vector Autoregressive (VAR) framework, it employs the SARIMA-type models which according to recent relevant literature tend to generate superior forecasts.

In turn, the contributions of this paper are described succinctly. First, we employ a country-of-origin approach in order to forecast tourism demand in Greece. Second, we forecast tourism demand based on both aggregated and disaggregated data on inbound tourist arrivals, using SARIMA-type models and we augment this specification by employing macroeconomic indicators of origin countries as explanatory variables. The present work constitutes an extension of existing literature in this area, as it is the first to employ both disaggregated data and macroeconomic indicators in tandem for the purpose of forecasting tourist arrivals.

Our forecasting exercises show that investigating tourism demand in Greece by considering macroeconomic indicators by country of origin offers an additional tool to decision makers (such as tourism policy makers and tourism providers in Greece) as it informs their practices and improves their forecasts. From a technical perspective, based on the Diebold-Mariano test, we show that the SARIMA specification which uses both disaggregated tourist arrivals data and macroeconomic variables does provide statistically significantly better forecasts compared to the SARIMA specification based on the aggregated tourist arrivals data. Results are very important, considering the perishable nature of the tourist product which renders necessary the choice of the best model to forecast tourist arrivals. In effect, this study serves as a new tool to policy makers and tourism businesses on how they should assess the macroeconomic developments in the tourism origin countries when planning the Greek tourism strategy and predicting future tourism earnings.

The rest of the paper is structured as follows. In section 2 we present a brief review of the existing literature. Section 3 describes the data, whereas Section 4 illustrates the forecasting models and provides a detailed explanation of the forecasting estimation procedure. Section 5 describes the adopted forecasting evaluation method. Section 6 analyses the empirical findings, before Section 7 concludes the study.

2. Brief review of the literature

It falls beyond the scope of this study to offer an extensive review of the related literature. However, it would be instructive at this point to overview certain key aspects raised in previous studies in order to position our research in this crowded literature. To this end, in the following paragraphs, we outline succinctly considerations which are mainly associated with the type of data, the model and its specification.

To begin with, we approximate tourism demand by tourism arrivals (i.e. in line with authors such as Dharmaratne, 1995; Smeral and Weber, 2000; Law, 2000; Burger *et al.*, 2001; Lim and McAleer, 2001a,b; Song and Witt, 2006; Athanasopoulos and Hyndman, 2008; Shen *et al.*, 2011; Gounopoulos *et al.*, 2012). Furthermore, contrary to the majority of the existing literature and yet in accordance with authors such as Kim and Moosa (2005) and Wan *et al.* (2013), we employ disaggregated data to forecast tourism demand as we also believe that this approach could provide policy makers with more detailed and diverse information.

Turning to the type of models employed by existing literature, we observe that not a single model is preferred. In fact, a battery of different models has been applied, such as (i) ARIMA (Autoregressive Integrated Moving Average) models[1], (ii) ECM (Error Correction Model) and VAR (Vector Autoregressive) models[2], (iii) ADL (Autoregressive Distributed Lag) models[3], (iv) TVP (Time-Varying Parameter) models (Song *et al.*, 2003), as well as, (v) Holt-Winters and other exponential smoothing methods[4].

Despite the non-consistent findings in terms of the best performing model used to forecast tourism demand, it seems that the most widely used and successful are the ARIMA-type models. Furthermore, one specific version of the ARIMA models, that of Seasonal ARIMA (SARIMA), has attracted considerable attention over the years due to its good performance which can be attributed to its ability to capture the seasonal character of tourism demand variables (see, indicatively, Song and Li, 2008; Brida and Risso, 2011; Hadavandi *et al.* 2011).

Next, we concentrate on studies which employ macroeconomic indicators in their analysis of tourism demand. It should be noted that a remarkable number of studies concentrate on the impact of macroeconomic indicators of origin countries on tourism demand at destination countries. For its most part though, literature in this field has

[1]See, *inter alia*, Kulendran and Wilson, 2000; Cho, 2001; Lim and McAleer, 2001a; Goh and Law, 2002; Cho, 2003; Kulendran and Witt, 2003; Chen, 2005; Vu and Turner, 2005; Kim and Moosa, 2005; Vu and Turner, 2006; Wong *et al*., 2007; Coshall, 2009; Santos, 2009; Brida and Risso, 2011; Gounopoulos *et al*., 2012; Zheng *et al.*, 2012; Wan *et al*., 2013.

[2]See for instance, Kulendran and Wilson, 2000; Song and Witt, 2000; Kulendran and Witt, 2003; Song and Witt, 2006; Wong *et al*., 2006; Wong *et al*., 2007.

[3] See indicatively, Song *et al.*, 2003; Wong *et al.*, 2007.

[4]See, for example, Lim and McAleer, 2001b; Chen, 2005; Vu and Turner, 2005; Yu *et al.*, 2007; Zheng *et al.*, 2012.

focused on demand factors and especially income (see, among others, Nicolau and Mas, 2005a,b; Wang *et al.*, 2006; Rudez, 2008; Lim *et al.*, 2009; Alegre *et al.*, 2010). This is mainly due to the fact that tourism is regarded as a luxury good and as such, it is expected to be heavily dependent on income (Chatziantoniou *et al.*, 2013; Wang, 2014). In short, the main finding of all these studies is that the level of income appears to exert a significant influence on tourism expenditure.

In support of this view, authors such as Papatheodorou et al. (2010), Page et al. (2012), as well as, Eugenio-Martin and Campos-Soria (2014) report negative effects on demand for tourism during periods of recession. Focusing on Greece, Dritsakis (2004) and Gounopoulos et al. (2012) emphasize income and unemployment (*i.e.* leading to loss of income) respectively, as two major indicators affecting demand for tourism in Greece. There is no doubt that income is indeed a key macroeconomic variable in the investigation of tourism demand.

Exchange rates constitute one additional demand factor typically employed by tourism demand studies. In general, evidence suggests that the level of the exchange rate can be credited with changes in the level of inbound tourism flows (see, *inter alia*, Bull, 1995; Hiemstra and Wong, 2002; Croes and Vanegas, 2005; Prideaux, 2005; Algieri, 2006; Saayman and Saayman, 2008; Wang, 2009). It should be noted that exchange rates can be also approximated by inflation differentials, on the basis of the Purchasing Power Parity notion. In this regard, Chang *et al.* (2013) point out that in the light of rises in inflation within the country of origin travellers typically contain their outbound tourism expenditure. This is anticipated, given that increased inflation weakens the domestic currency. Gounopoulos *et al.* (2012) investigate whether inflation differentials between origin and destination countries can influence inbound tourism. Results for Greece indicate that there is indeed a negative relation.

Demand for tourism can also be related to expectations about future economic conditions. According to authors such as Bull (1995) and Prideaux (2005) the Government has a key role to play in fashioning broader economic conditions and influencing expectations. Authors such as Kim *et al.* (2012) place heavy emphasis upon the effect of expectations about future income on demand for outbound tourism. It is important to note at this point that expectations about the future economic conditions can be reflected upon popular survey measures, such as the consumer confidence indicator (see, for example, Ludvigson, 2004). In close relation to this, authors such as Taylor and McNabb (2007) argue that both the consumer and the business confidence indicators have a key role to play in predicting recessions. Gounopoulos *et al.* (2012) also employ the consumer confidence index of origin countries as an approximation of their general economic conditions and investigate whether there is an impact on inbound Greek tourism.

Overall, in contrast with the narrow perspective usually encountered in existing literature, our study considers a broader set of macroeconomic indicators, comprising five macroeconomic indicators; namely, income, price level differentials, consumer confidence index, business confidence index, as well as, economic policy uncertainty (PUI) index. These indicators are specifically constructed to capture expectations about future economic conditions. To the effect that we make use of the ratio of domestic to foreign inflation rate (price level differential) we account for exchange rate issues, as well. With reference to the economic policy uncertainty index, this is developed by Baker *et al.* (2013) and has recently gained much prominence, as it is considered to be a very robust measure of policy-related uncertainty at both the fiscal and the monetary policy level (see, *inter alia*, Leduc and Liu, 2012; Antonakakis *et al.*, 2013; Colombo, 2013; Kang and Ratti, 2013; Pastor and Veronesi, 2013). By considering this relatively extensive set of macroeconomic indicators which could potentially influence inbound tourism demand, we aim to produce more accurate forecasts regarding inbound tourist arrivals in Greece from seven key origin countries.

3. Data description

In this study we use monthly tourist arrivals in Greece from seven key origin countries, namely, Canada, France, Germany, Italy, Spain, the UK and the US for a period extending from January 2003 to June 2013. In addition, we consider monthly macroeconomic variables for each of these countries. These variables are industrial production (IP) index, consumer price index (CPI), consumer confidence (CC) index, business confidence (BC) index and economic policy uncertainty (PUI) index.We also consider the Greek consumer price index, which is used to estimate the consumer price differentials between Greece and the origin countries. Consumer price differentials are estimated as $CPD_t = CPI_{GR,t} / CPI_{OCi,t}$, where GR denotes the Greek CPI and OCi stands for the CPI of the origin country i. Macroeconomic variables are denoted as $x_t^{(j)}$, for $j = 1,\ldots,5$, in the analysis. The selection of the macroeconomic variables is based on the criteria set out in Section 2. The choice of countries is influenced by two factors, namely that the countries of origins should be among the top countries of origin for Greece and that they should have data on the chosen macroeconomic variables.

Tourist arrivals data are obtained from Bank of Greece, data on economic policy uncertainty index are taken from Baker *et al.* (2013), whereas all other data on the remaining macroeconomic variables were extracted from *Datastream*®. The period of study is motivated by the data availability. The total number of months is T=126. Based on a starting sample of $\hat{T}=37$ observations, a total of $h=T-\hat{T}$=89 out-of-sample monthly forecasts consist the forecasting period (February 2006-June 2013)[5]. Descriptive statistics, as well as, plots of the variables under investigation are given in Table 1 and Figures 1, 2 and 3, respectively.

[TABLE 1 HERE]

[FIGURE 1 HERE]

[FIGURE 2 HERE]

[FIGURE 3 HERE]

Table 1 and Figure 1 suggest that, on average, for the study period, tourist arrivals in Greece from the chosen countries of origin contribute about 43% of the total tourist arrivals. This figure is even higher during the peak months of Greek tourism (i.e. from June until October) when the contribution of these countries to the total tourist arrivals fluctuates between 45% and 61%. These values signify the importance of these seven countries to the Greek tourism sector. Country-wise, we observe that Greece mainly attracts tourists from France, Germany, Italy and the UK.

Furthermore, Table 1 and Figures 1 and 2 provide evidence for the distributional and statistical properties of the variables under investigation. All tourist arrivals series (y_t) are non-stationary with a strong seasonal pattern[6]. Additionally, the first difference

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[5]More specifically, the first estimation period of the models is $\hat{T}$=37 months, i.e. from January 2003 until January 2006. The remaining h=89 months of our sample size are used for the evaluation period of the out-of-sample forecasts. In order to proceed to the first out-of-sample forecast (i.e. $t+1$ forecast or month 38) we estimate the models using the initial 37 months. For each subsequent out-of-sample forecast we add to the estimation period an additional month. For example, for the $t+2$ forecast we use $\hat{T}+1$ monthly observations. The total number of observations is $T=\hat{T}+h$. The out-of-sample phase has been selected in order to capture the period before, during and after the global financial crisis (as well as the Greek debt crisis).

[6] We have also used the HEGY unit root test (Hylleberg et al., 1990) and we find that the seasonal component of our series is stationary. Furthermore, we extract the seasonal component from our series using the TRAMO/SEATS procedure and we run unit root tests on the de-seasonlised series and the seasonal factor. The tests confirm that the series is non-stationary with a stationary seasonal component. Results are available upon request.

of the logarithmic transformation, $(1-L)(\log y_t)$, has a statistically significant autocorrelation pattern. In particular, the autocorrelation analysis confirms the existence of statistically significant autocorrelation and partial autocorrelation[7]; i.e. Box and Jenkins (1970), Box *et al.* (2008), Brockwell and Davis (2009), Ljung and Box (1978). Furthermore, the unit root tests show that the log-differences of monthly tourist arrivals are stationary. This holds for both the aggregate data, as well as, the disaggregated data by origin country. Therefore, the most appropriate model for the estimations is a SARIMA-type model.

Figure 3 shows the five macroeconomic variables which are employed in this study. We observe that the chosen indices are able to capture the economic conditions of the origin countries. For instance, the business confidence, consumer confidence and industrial production indices exhibit a clear trough in the Great Recession of 2007-09, whereas the economic policy uncertainty index reaches a peak during the same economic crisis. Similarly, the CPI differentials show a decreasing trend during the latter part of the study period, which coincides with the debt crisis in Greece and results in the significant reduction of the country's consumer price index.

4. Models' Specification

The purpose of this study is the evaluation of the forecasting accuracy of three different model specifications (i.e. forecasting exercises). First we forecast total tourist arrivals in Greece from the seven origin countries based on aggregate data (first specification). Next we forecast total tourist arrivals from these countries based on the disaggregated data by origin country (second specification). Finally, we forecast total tourist arrivals based on the disaggregated data by origin country and exploiting the predictive information provided by the exogenous macroeconomic variables (third specification).

The statistically significant autocorrelation pattern, the seasonality of the monthly data and the first-order integrated character of logarithmic transformation of tourist arrivals are best described by a SARIMA$(k,1,l)\left(k^{\bullet},l^{\bullet}\right)$ model[8]. Therefore, we estimate a set of SARIMA models for various orders of $k,l,k^{\bullet},l^{\bullet}$, and more

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[7]The results are available upon request.

[8] The k and l denote the number of lags for the autoregressive and the moving average polynomials, respectively. The k^* and l^* denote the number of lags for the seasonal autoregressive and the seasonal moving average polynomials, respectively.

specifically for $k=0,1,2$, $l=0,1,2$, $k^{\bullet}=0,1,2$, $l^{\bullet}=0,1,2$. In total, 81 variations of the SARIMA$(k,1,l)(k^{\bullet},l^{\bullet})$ model are estimated recurrently at each month for the out-of-sample period[9].

The incorporation of exogenous information (inclusion of macroeconomic variables) is utilized with the estimation of SARMAX$(k,l)(k^{\bullet},l^{\bullet})$ models, where X denotes the use of exogenous variables. The SARMAX models combine the auto-correlated and seasonal pattern of log-tourist arrivals with the information extracted exogenously from the macroeconomic variables. Therefore, we estimate a set of SARMAX(k,l)($k^{\bullet},l^{\bullet}$) models for various orders of $k,l,k^{\bullet},l^{\bullet}$, and more specifically for $k=0,1,2$, $l=0,1,2$, $k^{\bullet}=0,1,2$, $l^{\bullet}=0,1,2$. For each exogenous macroeconomic variable, $x_t^{(j)}$, for $j=1,...,5$, 81 variations of the SARMAX(k,l)($k^{\bullet},l^{\bullet}$) model are estimated recurrently at each month for the out-of-sample period. Thus, in total 405 SARMAX specifications are estimated for each of the h=89 out-of-sample months.

4.1. Seasonal Autoregressive Integrated Moving Average Model– SARIMA$(k,1,l)(k^{\bullet},l^{\bullet})$ Model

The Seasonal Autoregressive Integrated Moving Average Model with orders ($k,1,l$) and ($k^{\bullet},l^{\bullet}$), or SARIMA($k,1,l$)($k^{\bullet},l^{\bullet}$) is defined as[10,11]:

$$(1-A(L))(1-C(L))((1-L)(\log y_t)-\beta_0)=(1+B(L))(1+D(L))\varepsilon_t, \tag{1}$$

where $A(L)=\sum_{i=0}^{k}a_iL^i$, $C(L)=\sum_{i=0}^{k^*}c_iL^{12i}$, $B(L)=\sum_{i=0}^{l}b_iL^i$, $D(L)=\sum_{i=0}^{l^*}d_iL^{12i}$, L is the lag operator, $a_0=c_0=b_0=d_0=0$, $a_1,...,a_k,c_1,...,c_{k^*},b_1,...,b_l,d_1,...,d_{l^*},\beta_0$ are parameters for estimation, and $\varepsilon_t \sim N(0,\sigma_\varepsilon^2)$.

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[9]The certain parameter ranges of AR and MA orders for both seasonal and non-seasonal components rely on methods of orders' selection (Schwarz's, 1978 and Akaike's, 1974 information criteria) and correlogram diagnostics. We use the information criteria in order to set the upper bounds for the ranges of the dynamics included in the models.

[10]Originally the model is denoted as SARIMA($k,1,l$)($k^{\bullet},0,l^{\bullet}$), but for simplicity we have removed the zero term. The proposed framework can be defined either as a SARMA specification for the dependent variable $(1-L)(\log y_t)$ or as a SARIMA specification for the dependent variable $\log y_t$. In the latter case, the models can be stated as SARIMA with integrated order I(1), or SARIMAX($k,1,l$)($k^{\bullet},l^{\bullet}$).

[11]The log transformation stabilizes the variance of y_t, thus, it is preferred; see i.e. Lütkepohl and Xu (2012). The models' integration order is set to 1. For higher order of integration the forecasting accuracy deteriorates significantly.

The one-month-ahead tourist arrivals prediction by a SARIMA(k,1,l)($k^{\bullet}$,$l^{\bullet}$) is computed as:

$$y_{t+1|t} =$$

$$= \exp\begin{pmatrix} \log y_t + \beta_0 + \\ (C(L) + A(L) - A(L)C(L))((1-L)(\log y_{t+1}) - \beta_0) \\ + (D(L) + B(L) + B(L)D(L))\varepsilon_{t+1} + 0.5\sigma_{\varepsilon}^{2(t)} \end{pmatrix} \quad (2)$$

where $A(L) = \sum_{i=1}^{k} a_i L^i$, $C(L) = \sum_{i=1}^{k^*} c_i L^{12i}$, $B(L) = \sum_{i=1}^{l} b_i L^i$, $D(L) = \sum_{i=1}^{l^*} d_i L^{12i}$ .As, $\varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$, the $\exp(\varepsilon_t)$ is log-normally distributed, therefore the one-month-ahead tourist arrivals prediction is adjusted as $y_{t+1|t} = \exp(\log(y_{t+1|t}) + 0.5\sigma_{\varepsilon}^{2(t)})$.

4.2. Seasonal Auto-Regressive Moving Average Model with Exogenous Variables– SARMAX(k,l)($k^{\bullet},l^{\bullet}$) Model

The Seasonal Autoregressive Moving Average Model including exogenous variables with orders(k,l) and ($k^{\bullet}$,$l^{\bullet}$), or SARMAX(k,l)($k^{\bullet}$,$l^{\bullet}$) is defined as:

$$(1 - A(L))(1 - C(L))((\log y_t) - \beta_0 - \beta_1(\log x_{t-1}^{(j)})) = (1 + B(L))(1 + D(L))\varepsilon_t, \quad (3)$$

where $A(L) = \sum_{i=0}^{k} a_i L^i$, $C(L) = \sum_{i=0}^{k^*} c_i L^{12i}$, $B(L) = \sum_{i=0}^{l} b_i L^i$, $D(L) = \sum_{i=0}^{l^*} d_i L^{12i}$, L is the lag operator, $a_0 = c_0 = b_0 = d_0 = 0$, $a_1,...,a_k, c_1,...,c_{k^*}, b_1,...,b_l, d_1,...,d_{l^*}, \beta_0, \beta_1$ are parameters for estimation, and $\varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$. The exogenous variables $x_t^{(j)}$, for $j = 1,...,5$ are incorporated into the model in a lagged term in order to provide forecasting information.

The one-month-ahead tourist arrivals prediction by a SARMAX(k,l)($k^{\bullet}$,$l^{\bullet}$) is computed as:

$$y_{t+1|t} =$$

$$= \exp\begin{pmatrix} \beta_0 + \beta_1(\log x_t^{(j)}) + \\ (C(L) + A(L) - A(L)C(L))((\log y_{t+1}) - \beta_0 - \beta_1(\log x_t^{(j)})) \\ + (D(L) + B(L) + B(L)D(L))\varepsilon_{t+1} + 0.5\sigma_{\varepsilon}^{2(t)} \end{pmatrix} \quad (4)$$

where $A(L) = \sum_{i=1}^{k} a_i L^i$, $C(L) = \sum_{i=1}^{k^*} c_i L^{12i}$, $B(L) = \sum_{i=1}^{l} b_i L^i$, $D(L) = \sum_{i=1}^{l^*} d_i L^{12i}$.

For example, the forecast from the SARMA(1,1)(0,1) model is computed as:

$$y_{t+1|t} = \exp\begin{pmatrix} \beta_0 + \beta_1 \log x_t^{(j)} + \log x_{t-1}^{(j)} + a_1 \log y_t - a_1\beta_0 - a_1\beta_1 \log x_{t-1}^{(j)} \\ + d_1\varepsilon_{t-11|t} + b_1\varepsilon_{t|t} + b_1 d_1 \varepsilon_{t-12|t} + 0.5\sigma_{\varepsilon}^{2(t)} \end{pmatrix}, \qquad (5)$$

where $\varepsilon_{t-t^*|t}$ denotes the residual term at time t-t^* estimated based on the information set at time t.

4.3. Forecasting Total Tourist Arrivals (SARIMA Specification)

The SARIMA(k,1,l)($k^\bullet$,$l^\bullet$) specification is used to forecast the total number of tourist arrivals from the seven origin countries under investigations. Equation (1) is considered for y_t denoting the total tourist arrivals. From 81 variations of the SARIMA(k,1,l)($k^\bullet$,$l^\bullet$) model, the orders $k, l, k^\bullet, l^\bullet$ with the minimum value of the forecasting evaluation criteriain the out-of-sample period are selected (see Equations 6 and 7).

4.4. Forecasting Tourist Arrivals per Origin Country (Composite SARIMA Specification)

The SARIMA(k,1,l)($k^\bullet$,$l^\bullet$) specification is used to forecast the number of tourist arrivals from each of the seven origin countries separately. Equation (1) is considered for y_t denoting the tourist arrivals from each country separately. The forecast of the total tourist arrivals is the sum of the forecasts of tourist arrivals from each country. For each country, out of the 81 variations of the SARIMA(k,1,l)($k^\bullet$,$l^\bullet$) model, the orders $k, l, k^\bullet, l^\bullet$ that minimize the forecasting evaluation criteriain the out-of-sample period are selected.

4.5. Forecasting Tourist Arrivals per Origin Country Incorporating Information from Macroeconomic Variables (Composite SARMAX Specification)

The SARMAX(k,l)($k^\bullet$,$l^\bullet$) specification is used to forecast the number of tourist arrivals from each of the seven countries separately. Equation (3) is considered for y_t denoting the tourist arrivals from each country separately, and with the incorporation of exogenous variables $x_t^{(j)}$. The forecast of the total tourist arrivals is the sum of the forecasts of tourist arrivals from each country.

The 81 variations of the SARMAX(k,l)($k^{\bullet},l^{\bullet}$) model are estimated for each of the 5 explanatory economic variables, $x_t^{(j)}$, for $j=1,...,5$. Hence, in total for each country of origin, we estimate 5*81=405 SARMAX(k,l)($k^{\bullet},l^{\bullet}$) specifications. Each of the 405 SARMAX specifications are estimated for h=89 out-of-sample months. For each country, from the 405 SARMAX(k,l)($k^{\bullet},l^{\bullet}$) variations, the orders k,l, $k^{\bullet},l^{\bullet}$ and the $x_t^{(j)}$ with the minimum value of the forecasting evaluation criteriain the out-of-sample period are selected.

Table 2 presents the SARIMA(k,1,l)($k^{\bullet},l^{\bullet}$) and SARMAX(k,l)($k^{\bullet},l^{\bullet}$) specifications that minimize the forecasting evaluation criteria.

[TABLE 2 HERE]

5. Evaluation Framework

In this study we use two forecasting evaluation criteria, which are computed in the following form:

$$\text{Predicted Root Mean Squared Error: } \sqrt{h^{-1}\sum_{t=1}^{h}\left(y_{t+1}-y_{t+1|t}\right)^2}, \quad (6)$$

$$\text{Predicted Mean Absolute Error: } h^{-1}\sum_{t=1}^{h}\left|y_{t+1}-y_{t+1|t}\right|, \quad (7)$$

where $y_{t+1|1}$ denotes the one-month-ahead forecast of tourist arrivals, and h is the number of months in the out-of-sample period.

In addition, the statistical significance of the forecasts is investigated by the Diebold and Mariano (1995) statistic. Let us denote as $\Psi_{t(A)}$ the value of an evaluation criterion Ψ, for month t, based on the forecast of model A[12].The evaluation differential $\Psi_{t(A,B)}=\Psi_{t(A)}-\Psi_{t(B)}$ defines the difference of evaluation criteria of two competing models; i.e. models A and B. Diebold and Mariano (1995) proposed testing the null hypothesis, $H_0: E\left(\Psi_{t(A)}-\Psi_{t(B)}\right)=0$, that two models are of equivalent predictive ability against the alternative hypothesis, $H_1: E\left(\Psi_{t(A)}-\Psi_{t(B)}\right)<0$, that model A is of

[12]I.e., for the case that the evaluation criterion Ψ is the Root Mean Squared Error,then $\Psi_t=\left(y_{t+1}-y_{t+1|t}\right)^2$.

superior predictive ability compared to its competitor model B. The DM statistic for testing the null hypothesis is estimated as:

$$DM_{(A,B)} = \frac{\overline{\Psi}_{(A,B)}}{\sqrt{V\left(\overline{\Psi}_{(A,B)}\right)}}. \tag{8}$$

The average of evaluation differential is $\overline{\Psi}_{(A,B)} = h^{-1}\sum_{t=1}^{h}\Psi_{t(A,B)}$ and a consistent estimate of the variance of $\overline{\Psi}_{(A,B)}$ is computed as $V\left(\overline{\Psi}_{(A,B)}\right) = h^{-1}2\pi f_d(0)$, where $f_d(0) = (2\pi)^{-1}\sum_{i=-\infty}^{\infty}\gamma_d(i)$ is the spectral density of the loss differential at frequency zero. The DM statistic is approximately normally distributed for large samples of out-of-sample predictions, h. The DM statistic is also estimated as the standardized constant coefficient from regressing $\Psi_{t(A,B)}$ on a constant with heteroskedastic and auto-correlated consistent standard errors in the sense of Newey and West (1987). More information about the estimation of the Diebold-Mariano statistic is available in Xekalaki and Degiannakis (2010, pp. 387).

A negative sign of the DM statistic informs that model A is more accurate compared to model B. The *p*-value informs about the statistical significance between the forecasting accuracy of the competing models.

6. Empirical Findings

We consider the forecasting performance of three different model specifications, as described in Sections 4.3 to 4.5. Table 2 reports the results from the RMSE and MAEforecasting evaluation criteriafor each specification.

Table 2 shows that the highest forecasting error is observed in the forecasts made using the aggregate tourist arrivals data (SARIMA specification), with RMSE of 74,035 and MAE of 51,893. The composite forecasting based on the disaggregated data by the origin countries (composite SARIMA specification) is exhibiting a lower forecasting error, given that the RMSE is 69,296 and the MAE is 50,282. However, most prominent among these results is the finding that the lowest forecasting error is observed in the composite forecasts based on the disaggregated data with the use of exogenous macroeconomic variables (composite SARMAX specification), with RMSE=62,733 and MAE=45,711.[13]

Furthermore, we notice that both RMSE and MAE are lower for each country-specific forecast, although this does not hold true for the US. Another interesting finding reported in Table 2 is the fact that there is not a single macroeconomic variable that significantly improves the forecasting ability of the models. In fact, we observe that this is country specific, as for example, the best composite SARMAX specification for Canada is the one that include the consumer confidence index, whereas the best specification for Spain is the one that incorporates the industrial production index.

Next, we assess the best performing model based on the DM test. More specifically, Tables 3 and 4 present the DM statistic estimates for the $\Psi_t = \left(y_{t+1} - y_{t+1|t}\right)^2$ and $\Psi_t = \left|y_{t+1} - y_{t+1|t}\right|$ evaluation criteria, respectively.

[TABLE 3 HERE]

[TABLE 4 HERE]

As aforementioned, the null hypothesis of the DM testis that two models are of equivalent predictive ability, whereas the alternative hypothesis is that model A is of superior predictive ability compared to its competitor model B.

In all cases and for both loss functions the DM statistic in negative, implying that model A generates better forecasts than model B. Nevertheless, not all differences are significant. In particular, the tourist arrivals forecast from the composite SARIMA specification is not statistically more accurate compared to the SARIMA forecast. In addition, the tourist arrivals forecast from the composite SARMAX specification is not significantly more accurate compared to the forecast from the composite SARIMA specification. However, the most important finding is that the forecast of tourist arrivals from the composite SARMAX specification is statistically more accurate compared to the forecast from the SARIMA specification. Therefore, the DM statistics and their associated *p*-values reveal that the inclusion of economic variables in a SARIMA-type model provides tourist arrivals forecasts with statistically superior predictive ability.

Finally, we present the scatter plots in Figures 4 which provide a visual representation of the relationship between actual and predicted tourist arrivals.

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[13] Typical in forecasting studies is the comparison of candidate models with simple benchmark models; i.e. with/without drift random walk model, 1st order autoregressive model, etc. In our study, the forecasting ability of the naive benchmark models is statistically inferior. The results are available upon request.

[FIGURE 4 HERE]

It is clear from Figure4 that the composite forecast of tourist arrivals from composite SARMAX modelsproduces a rather slimmer plot (see the right panel of Figure4), as opposed to the plots produced by the forecast of the SARIMA and composite SARIMA specifications (see left and central panels, respectively). In addition, thecomposite forecast of tourist arrivals from composite SARMAX specification is observed to have fewer outliers.

7. Concluding remarks and policy implications

The aim of this study is to forecast, using SARIMA -type models, the one-month ahead tourist arrivals in Greece based on aggregate tourist arrivals data, disaggregated data by origin country, as well as, a set of macroeconomic indicators from the origin countries as explanatory variables. Our data comprise monthly tourist arrivals in Greece from seven key origin countries, namely, Canada, France, Germany, Italy, Spain, the UK and the US and the period of the study runs from January 2003 until June 2013. The monthly macroeconomic variables for each of these origin countries are, (i) the industrial production (IP) index, (ii) the consumer price level differentials between Greece and the origin country (CPD), (iii) the consumer confidence (CC) index, (iv) the business confidence (BC) index and (v) the economic policy uncertainty (PUI) index.

More specifically, in this study we first forecast total tourist arrivals in Greece from the seven origin countries based on aggregate data (SARIMA specification). Then, we forecast total tourist arrivals from these countries based on the disaggregated data by origin country (composite SARIMA specification). Finally, we forecast total tourist arrivals using the disaggregated data and incorporating exogenous macroeconomic variables (composite SARMAX specification). This is the first study to assess the forecasting accuracy of each SARIMA specification using the Diebold-Mariano test, based on two forecasting evaluation criteria, i.e. Predicted Root Mean Squared Error (RMSE) and Predicted Mean Absolute Error (MAE).

Prominent among the findings of the study is the fact that the origin of tourist arrivals is indeed a crucial factor when it comes to forecasting tourism demand. To be more explicit, results show that in each origin country, there is one single macroeconomic indicator which eventually stands out and can be conducive to better forecasts, while at the same time, this indicator may in fact vary among origin countries.

In this regard, we note that the consumer confidence index is important for producing better forecasts in Canada and the UK. By the same token, the price level is important for France and Germany, income is important for Italy and Spain, while economic policy uncertainty is important for the US. Thus, this study stresses the importance to incorporate a strenuous set of macroeconomic indicators by origin country as this apparently leads to better forecasts and better decisions.

Considering Greece, this finding is associated with several layers of analysis. First, with the exception of the business confidence indicator, all other indicators are rather crucial at predicting tourist arrivals in Greece. It follows, that policy makers who wish to produce better forecasts - at the aggregate level - may implement most of the indicators included in this study.

Second, at the country-specific level, policy makers could attain a rough yet strong indication about prospective tourist arrivals per origin country by simply considering the changes in the respective macroeconomic variables. For example, on the basis that higher levels of consumer confidence are typically related to higher demand for outbound tourism, monitoring the consumer confidence index in either Canada or the UK could provide useful predictive information regarding future arrivals of both Canadian and British tourists in Greece.

Third, given that outbound tourism factors are country-specific; this finding further exposes the necessity for policy makers to diversify their sources of tourism, as well as, their promoting activities. For example, given that price levels are important in terms of predicting tourist arrivals in Greece from France and Germany, high levels of inflation within the EMU should be accompanied by an effort from policy makers in Greece to convince potential French and German tourists that Greece can be a relatively low-cost destination. It should be noted however, that adopting the appropriate strategy is not always as straightforward as in the case of relative prices. To illustrate this point, we refer to our results for Italy and Spain. In particular, we find that the industrial production index in both countries is a key factor in producing better forecasts regarding tourist arrivals in Greece. A worsening of the industrial production index might lie on more persistent unfavourable developments in an economy - compared to a rise in the level of prices, which can be temporary - suggesting that policy makers in Greece will probably not be able to successfully attract tourists from these two countries by simply offering more competitive prices. However, this reverts back to our initial argument that diversifying the sources of tourism and/or promoting activities should indeed be a cardinal strategic objective.

Turning to the forecasting method itself, our forecasting exercises show that the composite SARMAX specification does provide statistically significantly better forecasts compared to the SARIMA specification. This finding holds for both loss functions. Another important finding that is reported in this study is the fact that there is not a single macroeconomic variable that significantly improves the forecasting ability of the models. In fact, the best variable is country specific; as for example, the best composite SARMAX specification for Canada is the one that includes the consumer confidence index, whereas the best performing specification for Spain is the one that incorporates the industrial production index.

Tourism is a key economic activity in Greece and a major source of domestic income with direct implications regarding its influence on the country's overall growth potential. This fact underscores the necessity for accurate tourist arrivals forecasts. The tourist product has a perishable nature and therefore, the choice of the best model is of major importance. Thus, our findings have important implications when it comes to developing the appropriate tourism strategy plan.

In retrospect, policy makers do produce better forecasts by considering disaggregated data and macroeconomic indicators. Furthermore, identifying key macroeconomic indicators in each origin country allows for both a better understanding of country-specific issues concerning demand for outbound tourism and a better targeting of promoting efforts concerning the tourism product of the destination country. Most importantly, this study provides evidence that it is important for destination countries to diversify their sources of tourism to account for the different factors that may impact tourist arrivals levels.

Potential avenues for future research could also include other types of disaggregation of inbound tourist arrivals by mode of travel or duration of stay, as these choices may be also impacted by the macroeconomic conditions in origin countries. What is more, future studies should further concentrate on the formulation of models which purport to combine many macroeconomic indicators in their structure. On a final note, apart from specifically focusing on one-step-ahead forecasts, attention should also be directed towards m-steps ahead forecasting.

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Figures

Figure1. Aggregate tourist arrivals from origin countries and their contribution to the total tourist arrivals. The sample period runs from January, 2003 until June, 2013.

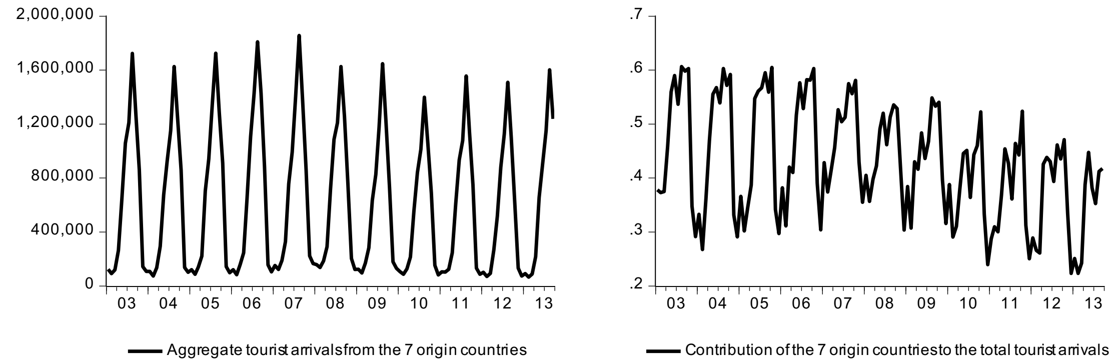


Figure2. Tourist arrivals in Greece from each origin country. The sample period runs from January, 2003 until June, 2013.

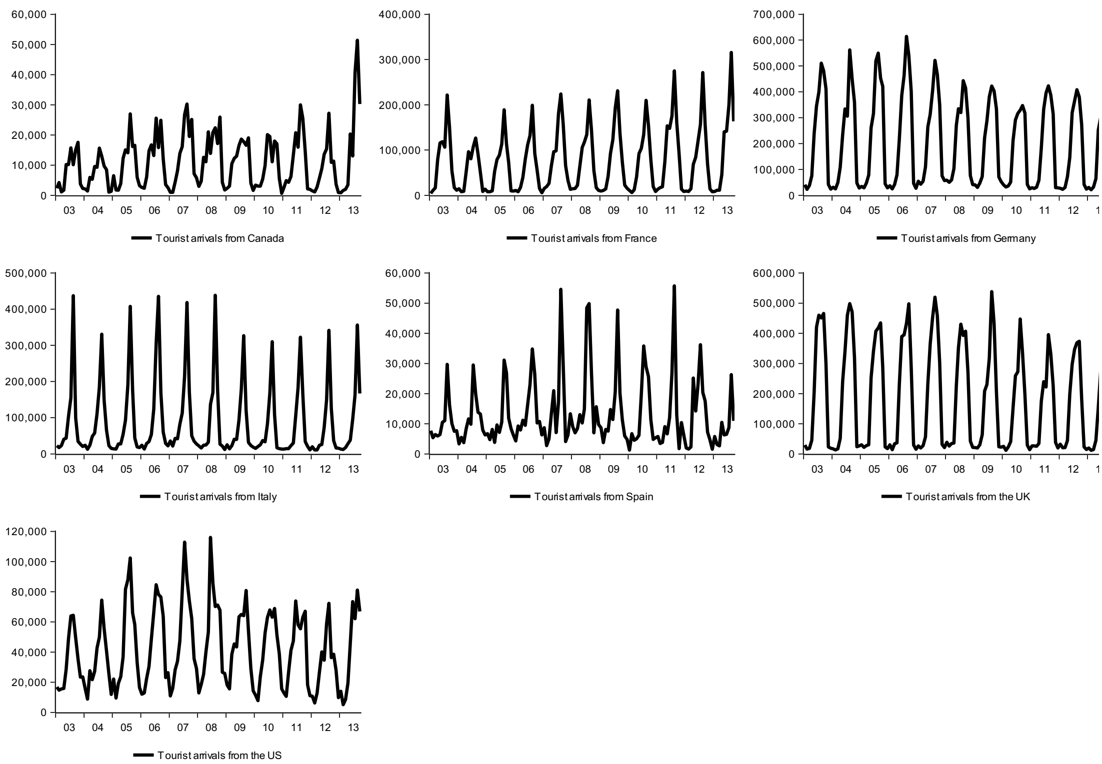
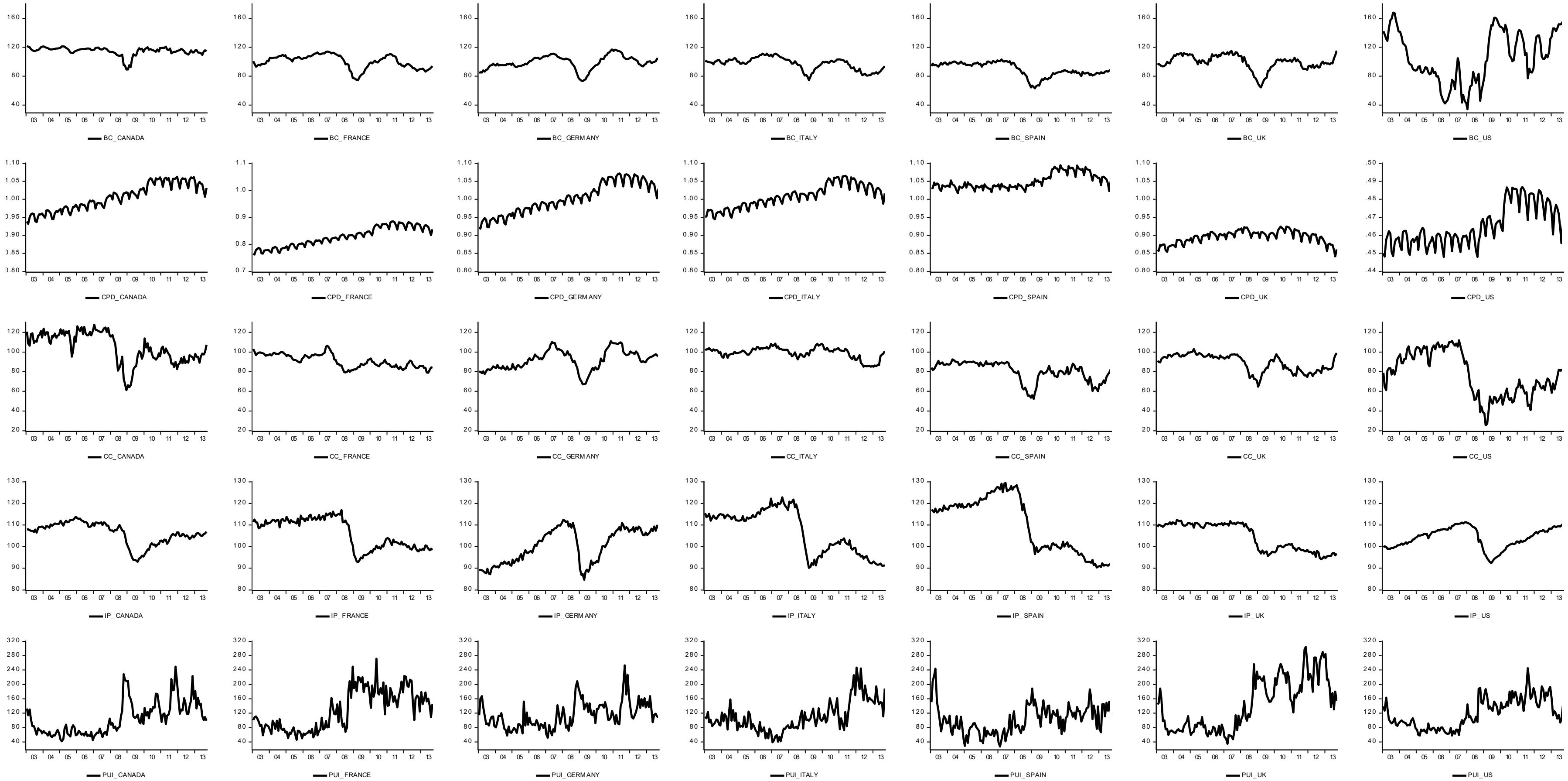
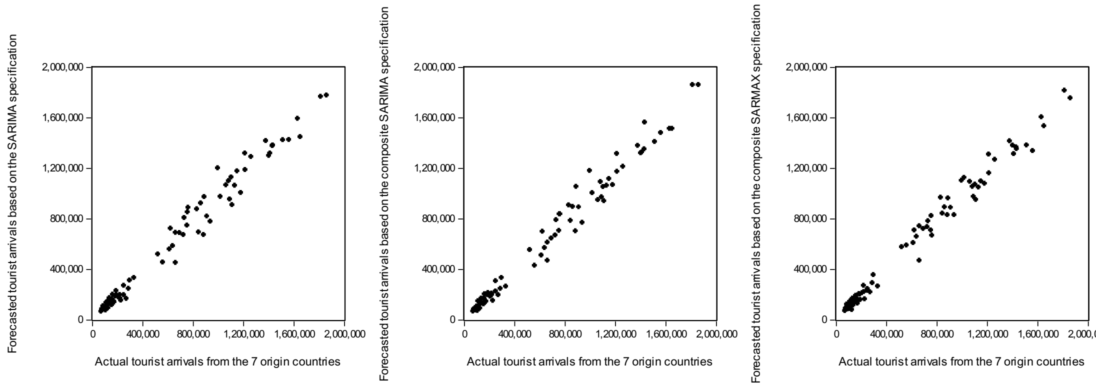


Figure3. Macroeconomic variables of the seven origin countries. The sample period runs from January, 2003 until June, 2013.



Reading along the rows we show the following macroeconomic variables: Business Confidence (BC) index, Consumer price differentials (CPD), Consumer confidence (CC) index, Industrial production (IP) index and Economic policy uncertainty (PUI) index.
Reading down the columns we show the macroeconomic variables for the following origin countries: Canada, France, Germany, Italy, Spain, the UK and the US.

Figure4. Scatter plots of the three forecasting specifications. The sample period of the out-of-sample forecasts runs from February, 2006 to June, 2013.



Note: Columns from left to right present the scatter plots for the forecast from the SARIMA specification, the composite SARIMA specification and the composite SARMAX specification. The x-axes (y-axes) show the actual (predicted) values.

Tables

Table 1. Descriptive statistics of the series under investigation. The sample period runs from January, 2003 until June, 2013.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF-stat
				Tourist arrivals from origin countries				
Canada	10987.810	51407.000	626.000	9131.716	1.233	5.243	59.740***	0.718
France	77320.280	315720.000	4092.000	70868.500	0.958	3.324	20.281***	0.268
Germany	206528.300	614134.000	21002.000	174764.700	0.411	1.715	12.513***	-0.770
Italy	87264.190	438110.000	10729.000	106154.100	1.877	5.807	118.062***	-0.333
Spain	12988.230	55705.000	1250.000	11179.630	1.875	6.509	141.764***	-0.434
UK	182617.800	538093.000	11475.000	170887.300	0.457	1.659	14.163***	-1.375
US	41842.910	115923.000	5075.000	25612.050	0.554	2.501	7.946**	0.064
Aggregate	619549.200	1855999.000	66036.000	532613.600	0.583	2.006	12.615***	-0.476
Contribution	0.429	0.607	0.223	0.104	0.016	1.985	5.546*	-3.217***
				Log-difference of tourist arrivals from origin countries				
Canada	0.020	1.829	-2.174	0.775	-0.440	3.521	5.567*	-6.003***
France	0.029	1.767	-2.006	0.731	-0.255	3.287	1.820	-5.896***
Germany	0.019	1.414	-2.378	0.722	-1.356	5.685	77.680***	-5.559***
Italy	0.016	1.445	-1.870	0.707	-0.545	2.602	7.180**	-7.100***
Spain	0.003	2.401	-2.004	0.748	0.165	3.356	1.255	-7.707***
UK	0.019	2.114	-2.590	0.874	-0.792	4.739	29.489***	-5.526***
US	0.011	1.149	-1.303	0.487	-0.184	2.813	0.907	-5.216***
Aggregate	0.018	1.160	-1.843	0.641	-0.999	4.173	28.622***	-5.699***

***,**,* indicate significance at 1%, 5% and 10% level, respectively.
Aggregate refers to the total tourist arrivals from the seven origin countries.
Contribution refers to the contribution of the aggregate tourist arrivals from the seven origin countries to the total tourist arrivals of Greece.

Table 2. Forecast accuracy tests.

Country of Origin	SARIMA Specification	Forecast Evaluation Criteria: $\sqrt{h^{-1}\sum_{t=1}^{h}\left(y_{t+1}-y_{t+1\|t}\right)^2}$	Forecast Evaluation Criteria: $h^{-1}\sum_{t=1}^{h}\left\|y_{t+1}-y_{t+1\|t}\right\|$
Aggregate tourist arrivals (SARIMA specification)			
Total Forecast	SARIMA(2,1,0)(1,1)	74,035	51,893
Disaggregated tourist arrivals without exogenous macroeconomic variables (composite SARIMA specification)			
Composite Forecast	*The average forecast from the models below*	69,296	50,282
Canada	SARIMA(1,1,1)(0,2)	5,250	3,611
France	SARIMA(0,1,1)(1,1)	20,241	13,597
Germany	SARIMA(0,1,0)(1,1)	40,132	26,352
Italy	SARIMA(2,1,0)(0,2)	29,789	16,645
Spain	SARIMA(2,1,0)(0,2)	8,370	5,674
UK	SARIMA(0,1,1)(1,1)	38,831	23,126
US	SARIMA(1,1,2)(0,2)	**12,843**	**9,218**
Disaggregated tourist arrivals with exogenous macroeconomic variables (composite SARMAX specification)			
Composite Forecast	*The average forecast from the models below*	**62,733**	**45,711**
Canada	SARMAX(1,0)(0,2)-CC	**4,906**	**3,480**
France	SARMAX(2,0)(1,1)-CPD	**18,893**	**12,926**
Germany	SARMAX(0,1)(1,0)-CPD	**34,501**	**24,592**
Italy	SARMAX(0,0)(1,1)-IP	**22,483**	**13,848**
Spain	SARMAX(0,0)(0,2)-IP	**6,941**	**5,105**
UK	SARMAX(1,0)(1,1)-CC	**35,814**	**22,486**
US	SARMAX(1,1)(1,0)-PUI	12,956	9,353

Values report number of tourist arrivals.
Bold face fonts present the best performing model.
Consumer confidence (CC) index, Consumer price differentials (CPD), Industrial production (IP) index and Economic policy uncertainty (PUI) index

Table 3. The DM test statistics for testing the null hypothesis that Model A is of equal predictive ability as Model B. The evaluation criterion is based on the squared predicted error; $\Psi_t = \left(y_{t+1} - y_{t+1|t}\right)^2$.

Model A	Model B	DM Statistic	*p*-value
Forecast from composite SARIMA	Forecast from SARIMA	-0.985	0.3272
Forecast from composite SARMAX	Forecast from composite SARIMA	-1.344	0.1824
Forecast from composite SARMAX	Forecast from SARIMA	-2.669	0.0090

Table 4. The DM test statistics for testing the null hypothesis that Model A is of equal predictive ability as Model B. The evaluation criterion is based on the absolute predicted error; $\Psi_t = \left|y_{t+1} - y_{t+1|t}\right|$.

Model A	Model B	DM Statistic	*p*-value
Forecast from composite SARIMA	Forecast from SARIMA	-0.448	0.6549
Forecast from composite SARMAX	Forecast from composite SARIMA	-1.293	0.1992
Forecast from composite SARMAX	Forecast from SARIMA	-3.534	0.0007