THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

WP 37_09

Massimiliano Castellani
University of Bologna, Italy
and
The Rimini Centre for Economic Analysis, Italy

Maurizio Mussoni
University of Bologna, Italy
and
The Rimini Centre for Economic Analysis, Italy

Pierpaolo Pattitoni
University of Bologna, Italy

AIR PASSENGERS AND TOURISM FLOWS: EVIDENCE FROM SICILY AND SARDINIA

The Rimini Centre for Economic Analysis
Legal address: Via Angherà, 22 – Head office: Via Patara, 3 - 47900 Rimini (RN) – Italy
www.rcfea.org - secretary@rcfea.org

Air Passengers and Tourism Flows: Evidence from Sicily and Sardinia

February 14, 2010

Massimiliano Castellani[1], Maurizio Mussoni[2], Pierpaolo Pattitoni[3]

Abstract

Tourism plays an important role in the economies of many Mediterranean countries, since it is a crucial driver of economic growth, job creation, and income. For this reason many countries set up a wide variety of programs and policies to support the development of this economic sector. It is therefore very important, for scholars and policy makers, explaining and forecasting tourism demand. Using air passengers flows as proxy variables for tourist arrivals, we set up some VAR model specifications in order to investigate the monthly time series 2003-2008 of arrivals to the most important Italian islands, Sardinia and Sicily. Our results show a significant inter-temporal relationship among tourism flows. Furthermore, our findings reveal that both meteorological variables (atmospheric temperatures and raining days) and exchange rates (Dollar-to-Euro and Yen-to-Euro) can improve the explanatory and forecasting power of VAR models.

JEL Classification: L93, R58, C32.

Key words: Airports, Air transportation, VAR model.

1. Introduction

Tourism plays an increasingly important role in the economies of many Mediterranean countries, since it is a crucial driver of economic growth, job creation, and income. Tourism in Mediterranean

[1] Department of Economics, University of Bologna, Bologna, Italy and The Rimini Centre for Economic Analysis (RCEA), Rimini, Italy. E-mail: m.castellani@unibo.it.

[2] Department of Economics, University of Bologna, Bologna, Italy and The Rimini Centre for Economic Analysis (RCEA), Rimini, Italy. E-mail: maurizio.mussoni@unibo.it.

[3] Faculty of Economics, University of Bologna, Forlì and Rimini, Italy. E-mail: pierpaolo.pattitoni@unibo.it.

countries is mostly based on coastal and island resorts. According to the European Statistics Institute (Eurostat), the number of total arrivals to the European-Mediterranean Countries (EMCs), i.e. Greece, Spain, France, Italy, Cyprus, Malta, Slovenia, Croatia, and Turkey, in 2007 has been estimated equal to 399,532,000. For this reason many countries set up a wide variety of programs and policies to support the development of this economic sector. Focusing on Italy, we point out that the number of total arrivals in 2007 has been estimated equal to 96,150,000 (24% of the total number for EMCs). In particular, Sicily and Sardinia both count for about 7% of the total number (5% for Sicily, 2% for Sardinia). It is worth noting that the number of employed persons in tourism sector for the EMCs in 2007 has been equal to 9,807,000, 24% of which have been employed in Italy (corresponding to a number of 2,322,200). Hence we observe a certain degree of consistency between the Italy-to-EMCs arrivals ratio and the Italy-to-EMCs employment ratio. Furthermore we observe a similar evidence for all the remaining EMCs too. This evidence may be interpreted as a stylized fact: in tourism sector the EMCs adopt a quite homogenous production technology.

Considering the importance of tourism in EMCs economies, it is important both for policy makers and destination managers taking appropriate decisions concerning public investments (supply of public goods), and for tourism firms choosing carefully their investments (supply of private goods). Since tourism is well known to be a demand-driven economic sector, it may be interesting for tourism operators being capable to explain and forecast tourism demand, which is usually measured by tourism flows, i.e. arrivals and overnight stays. For this reason, several research works propose numerous approaches to tourism demand modeling and forecasting.

Gil-Alaña, Cuñado and Perez De Gracia (2008) propose some econometric models in order to analyze the arrivals to Canary Islands, considering both the cases of deterministic and stochastic seasonality in the time series. Comparing all models in terms of their forecasting ability, their results show that a model with seasonal dummy and AR(1) errors yields the best results.

Yorucu (2003) analyzes the forecast accuracy of four forecasting methods (Actual Statics, Double Exponential Smoothing, Holt Winters and Autoregressive Moving Averages-ARMA) for tourism arrivals to North Cyprus and Malta in the period 1976-1995. Their results show that Holt Winters and ARMA methods are the best forecasting methods in most of the cases.

Cho (2003) proposes three forecasting methods (Exponential Smoothing, ARIMA and Artificial Neural Networks) to forecast the number of arrivals to Hong Kong. His analysis shows that the Neural Networks approach produces the best forecasts. Song, Smeral, Li and Chen (2008) analyze the forecasting accuracy of five alternative econometric models for forecasting the quarterly international tourism demand. Their results show that the time-varying parameter model provides the most accurate short-term forecasts, whereas the naïve model performs best in long-term forecasting up to two years.

The above short list of research works shows that there is not a single forecasting technique that constantly outperforms the others in all the circumstances (Song and Li, 2008; Song *et al*, 2008). Using air passengers flows as proxy variables for tourist arrivals, we set up some Vector Autoregressive (VAR) model specifications in order to investigate the monthly time series 2003-2008 of arrivals to the most important Italian islands, that is Sardinia and Sicily. The choice of using air passengers flows as proxy variables for tourist arrivals is quite common in the literature. In fact, the ratio between tourist arrivals and the number of total air passengers, which are recorded in tourism destinations' airports, generally is a stable ratio through the time. It is therefore always possible to compute tourism arrivals once air passengers arrivals are known. Moreover, the main advantage of using air passengers data with respect to other data sources is that generally they are recorded by a public authority (ENAC in Italy) and are, consequently, more reliable. In particular, we focus our analysis on four major airports: Cagliari and Olbia in Sardina, Catania and Palermo in Sicily. We do not take into account Alghero (in Sardinia) and Trapani (in Sicily) because they are low-traffic airports, and they have been operating as commercial airports only in the last few years.

We contribute to the existing empirical literature on tourism demand modeling and forecasting in some ways. First, we focus on the two major islands of the Mediterranean area, which represent a large share of tourism flows in Europe, in particular in Italy. Furthermore, analyzing two islands allows us to observe high-quality data. In fact, tourists can reach these destinations only by airplanes or ferries, thus incoming passengers are recorded by a public authority for security reasons. The same is not true for other tourism destinations which can be reached, for example, by cars and trains. Second, we propose a more parsimonious VAR model specification, which allows for gaps in the lag structure. This VAR specification on the one hand yields a relevant degree-of-freedom saving; on the other hand, it allows to take into account the seasonality of arrivals time series. Indeed, both the degree-of-freedom saving and the seasonality are crucial aspects given the small sample we had at our disposal and its structural characteristics. Third, we propose three sets of exogenous variables (exchange rates, raining days and atmospheric temperatures) to be included in our VAR models. Since all these exogenous variables are often used as covariates in structural models, we want to test their contribution to forecasting tourism arrivals to Sardinia and Sicily. Finally, even if we focus our analysis on Sardinia and Sicily islands, we believe that a VAR approach like the one we propose in this paper may be appropriate whenever modeling and forecasting any destination tourism flows, given that in VAR models the inter-temporal relationships between time series are explicitly modeled.

The paper is structured as follows: Section 2 describes the proposed econometric models, Section 3 presents the results, while the final Section concludes the paper.

2. Econometric Models

We use a Vector Autoregressive approach (VAR) to model and forecast future values of air passengers arrivals to Cagliari, Olbia, Catania and Palermo airports, with monthly data relative to the period January 2003-December 2008. Several articles (e.g. Sims, 1980) point out that one advantage of VAR models over univariate time series models, or over simultaneous equations structural models, is that they yield more accurate forecasts.

The endogenous and exogenous variables we use in our analysis are the following ones:

- arrivals to Cagliari, Olbia, Catania and Palermo airports, defined as the natural logarithm of the monthly air passengers time series for each airport;
- exchange rates, defined as the natural logarithm of the monthly Yen-to-Euro and Dollar-to-Euro exchange rates;
- raining days in Cagliari, Olbia, Catania and Palermo, defined as the number of raining days per month in each airport;
- atmospheric temperatures in Cagliari, Olbia, Catania and Palermo, defined as the average atmospheric temperatures (in Celsius degrees) per month in each airport.

We select the exogenous variables to be included in our VAR model (exchange rates, raining days, atmospheric temperatures) according to theoretical and practical considerations. Specifically, we believe that air passengers arrivals are related to lagged exchange rates because of international travelers. In fact, the main business activity of these four airports is related to tourism flows. Since exchange rates are one of the determinants of international tourism demand, we suppose that they can affect international tourist arrivals. Given that the most of international tourist arrivals to Sicily and Sardinia is from Europe (in 2007 about 79.69% of the total international tourist arrivals were from the European Union), the most relevant exchange rates to be considered should be the Dollar-to-Euro and Yen-to-Euro exchange rates. However, as a robustness check, we tried several models by taking into consideration both the UK-Pound-to-Euro exchange rate and the BCE nominal effective exchange rate, which is based on weighted averages of bilateral Euro exchange rates against the 21 major trading partners of the Euro area. In this way, we found that our results are robust to the inclusion of these further exchange rates, given that they do not improve either the explanatory or the predictive power of our model. Furthermore, we use lagged values of the exchange rates because generally holidays are planned in advance.

We also believe that expected meteorological conditions may help in modeling and forecasting future values of air passengers arrivals. We therefore use the twelve-months lagged values of raining days and atmospheric temperatures as proxy variables for the expected meteorological conditions, which is a consistent choice with a naïve expectation scheme.

Figure 1 shows the plots for each series of log-arrivals. All series exhibit a clear trend and a seasonal pattern. This evidence is further confirmed by the month-plots, that show the pattern of each specific month for each series of log-arrivals. In particular, arrivals tend to be concentrated during the summer (June, July, August and September) and to reach the lowest values during the winter (January and February). Furthermore, the month-plots show the existence of a positive trend in the arrivals observed in the same month one year apart.

[Insert Figure 1 approximately here]

In order to analyze the statistical significance of the estimated coefficients, all of the components in the VAR model are required to be stationary. Hence, in Table 1 we present the unit root tests for all the endogenous and exogenous variables. For seasonal variables (log-arrivals, raining days and atmospheric temperatures) we performed both the Canova-Hansen test for seasonal unit root (Canova and Hansen, 1995) and the KPSS test (Kwiatkowski *et al*, 1992). For non-seasonal variables (log-exchange rates) we only performed a KPSS test. We found evidence of a unit root for log-exchange rates Dollar-to-Euro and Yen-to-Euro (US/EUR and JP/EUR) but not for their first differences. We therefore took the first differences of log-exchange rates in subsequent analysis. All remaining variables' tests did not lead to rejection of the null hypothesis of regular and seasonal stationarity after we properly accounted for deterministic trend and seasonal effects where needed. Thus we did not take the first differences of log-arrivals, raining days and atmospheric temperatures.

[Insert Table 1 approximately here]

In order to determine the appropriate lag length of our VAR model, we employ three multivariate information criteria. Table 2 shows the optimal lag order selection according to the Akaike (AIC), Schwartz (BIC) and Hannan-Quinn (HQC) information criteria, computed from

VARs of orders from 1 to 12. In this case, both AIC and HQC criteria select a VAR(12) as optimal model, while BIC criterion chooses a VAR(1) model.

[Insert Table 2 approximately here]

Accordingly, we first propose the following model specification:

$$y_t = A_1 y_{t-1} + Bx_t + u_t \tag{1}$$

where y_t is a 4×1 vector containing the 4 endogenous variables (i.e. the arrivals to the 4 airports), x_t is a 13×1 vector containing a constant, a linear trend and 11 seasonal dummies, u_t is a 4×1 vector of error terms, A_1 and B are matrices of coefficients. Since we have 4 equations in the model, each with 1 lag of the variables, a total of 68 parameters have to be estimated. Considering a model with 12 lags of the variables, we should estimate a total of 244 parameters. For our relatively small sample, this would result in consuming many degrees of freedom. Since we are dealing with monthly data, characterized by a strong seasonal component, we therefore propose the following alternative model specification:

$$y_t = A_1 y_{t-1} + A_{12} y_{t-12} + Bx_t + u_t \tag{2}$$

in which we allow for gaps in the lag structure. In fact, we do not include all the consecutive lags for any given variable, but only the 1st and the 12th lags. This new model specification needs for 84 parameters to be estimated for the entire model, allowing to save 160 degrees of freedom.

3. Empirical Analysis Results

In this Section we present the main results of our analysis. Table 3 shows F-tests for zero restrictions on all lags of each variable in VAR specifications 1 and 2. Since for the first model specification we are testing single hypotheses involving one coefficient at a time, these hypotheses could also be tested using the usual t-test (yielding the same conclusions). We observe that arrivals to all the airports are explained by their own lagged values. Furthermore, results of model specification 2 show that arrivals to each airport are partially explained also by lagged values of arrivals to other airports. This may suggest a certain degree of inter-temporal interdependence among passengers arrivals. In particular, arrivals to Cagliari airport Granger-cause (Granger, 1969) arrivals to all the other airports. Actually, this causality is unidirectional in all cases except from one. In fact, arrivals to Catania airport are found to Granger-cause arrivals to Cagliari airport too, suggesting a bi-directional feedback between these two airports. Accordingly, it may be said that arrivals to Cagliari airport are strongly exogenous in all equations except for Catania airport.

[Insert Table 3 approximately here]

In Table 4 we re-estimate the two model specifications including among regressors three sets of exogenous variables. In particular, we include the 3rd lag of the log-difference of two exchange rates, Dollar-to-Euro and Yen-to-Euro (US/EUR and JP/EUR), and the 12th lag of raining days and atmospheric temperatures in Cagliari, Olbia, Catania and Palermo. Our goal is to test the contribution of these exogenous variables to our model. Besides the F-tests for zero restrictions on all lags of each variable in VAR model, a Likelihood Ratio test is presented at the bottom of each set of estimates. The null hypothesis is that the true parameters values are equal to zero, in all equations of VAR models, for the omitted exogenous variables. The results show that all the exogenous variables considered, except for raining days in VAR(1) specification, are slightly significant (p-value < 0.1) in explaining the log-arrivals to the airports of the analyzed Mediterranean islands. Therefore, it seems that these variables convey some information to determine the inter-temporal behavior of air passengers arrivals. Considering a lag of three months for the log-difference of the exchange rates and twelve months for the meteorological variables may seem to be an arbitrary choice. Thus we re-estimated all the models considering different lag orders as a robustness check. Since results are not qualitatively different from those we report, we do not present them.

[Insert Table 4 approximately here]

Considering the out-of-sample period from January 2009 to May 2009, in Table 5 we present some measures of the overall accuracy of arrivals forecasts for each airport. In particular we compute the Root Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE) and the Theil's U (Theil, 1966). Letting y_t be the arrivals at time t, f_t a forecast of y_t and $e_t = y_t - f_t$ the forecast error, the three forecast accuracy measures are defined as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2} \quad (3)$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} 100 \frac{|e_t|}{y_t} \quad (4)$$

$$U = \sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\left(\frac{y_{t+1}-f_{t+1}}{y_t}\right)^2 \left[\frac{1}{T}\sum_{t=1}^{T-1}\left(\frac{y_{t+1}-y_t}{y_t}\right)^2\right]^{-1}} \quad (5)$$

From these definitions we infer that the more accurate are the forecasts the lower are the values of these three measures. In particular, Theil's U has a minimum value of 0, and can be thought of as the ratio of the RMSE of the selected model over the RMSE of a naïve model for which $y_{t+1} = y_t$ for all t. Since for the naïve model $U = 1$, values less than 1 denote a forecast improvement, while values greater than 1 denote a forecast worsening. Our forecast evaluation measures show that the best model for forecasting arrivals to Cagliari and Olbia airports includes one lag of the endogenous variables, and the 12th lag of atmospheric temperatures. Arrivals to Catania airport are better forecasted including in the model the 3rd lag of the log-difference of JP/EUR and US/EUR exchange rates, and the 1st and 12th lags of the endogenous variables. The best model to forecast arrivals to Palermo is the simpler model with the 1st and 12th lags of the endogenous variables, without any exogenous variables. Overall, considering all the airports and all the forecast evaluation measures, the best model for forecasting includes one lag of the endogenous variables and the 12th lag of atmospheric temperatures.

[Insert Table 5 approximately here]

4. Conclusions

Given the importance of tourism for the economies of many Mediterranean countries, it is important for scholars and policy makers being capable to appropriately explain and forecast tourism demand. In this paper we used air passengers flows as proxy variables for tourist arrivals, and we set up some VAR model specifications in order to investigate the monthly time series of arrivals to Sardinia and Sicily in the period 2003-2008.

The proposed VAR models allowed us to show the existence of a certain degree of inter-temporal interdependence among passengers arrivals to all the airports, and that both meteorological variables and exchange rates are slightly significant in explaining tourism arrivals.

However, as far as forecasting accuracy is concerned, our results confirm that there is not a single method that constantly outperforms the others. Specifically, our forecast evaluation measures show that the best model for forecasting arrivals to Cagliari and Olbia airports includes one lag of the endogenous variables and the 12th lag of atmospheric temperatures. The best model for arrivals to Catania airport includes the 3rd lag of the log-difference of JP/EUR and US/EUR exchange rates and the 1st and 12th lags of the endogenous variables. Arrivals to Palermo airport are better forecasted by a simpler model with the 1st and 12th lags of the endogenous variables, with no exogenous variables. Overall, the best model for forecasting includes one lag of the endogenous variables and the 12th lag of atmospheric temperatures.

It is common knowledge that time series frequency may affect the model selection. If this is the case for tourism arrivals to Sicily and Sardinia airports, future research may explore if non-linear models are more appropriate when daily data are analyzed.

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Figure 1. Log-arrivals to Cagliari, Olbia, Catania and Palermo airports (left side) and the corresponding month-plots (right side).

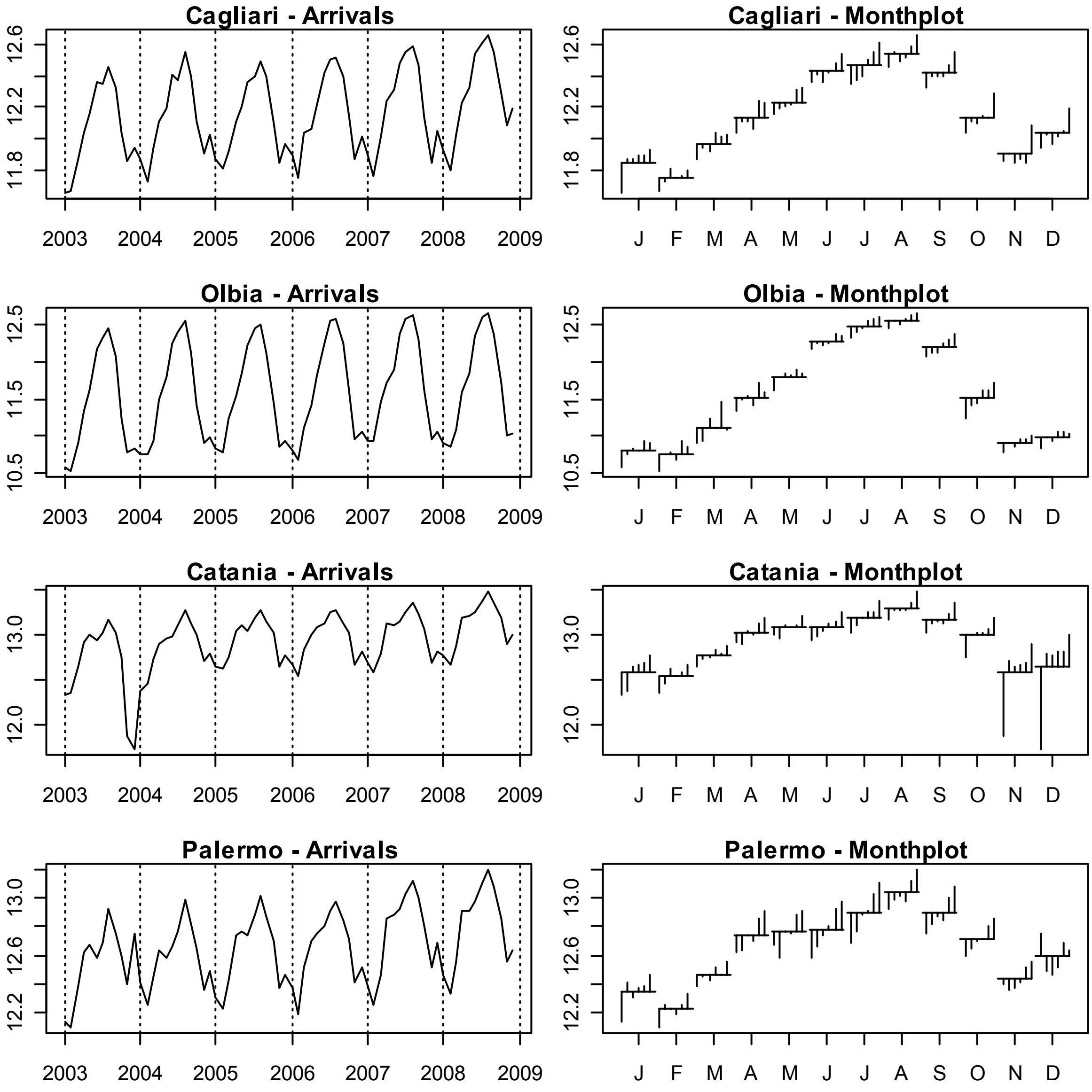

Table 1. Unit-root tests for all variables. For log-arrivals, raining days and atmospheric temperatures both the Canova-Hansen test for seasonal unit root (Canova and Hansen, 1995) and the KPSS test (Kwiatkowski *et al*, 1992) are presented. For log-exchange rates and their first differences only a KPSS test is presented. Linear trend (t-test) and seasonal effects (F-test for joint significance of seasonal dummies) are tested on the basis of an auxiliary regression. In both cases, heteroskedasticity and autocorrelation consistent standard errors are used.

Log-arrivals	Cagliari	Olbia	Catania	Palermo
Linear Trend	5.152	4.323	5.132	7.894
Result	Linear Trend	Linear Trend	Linear Trend	Linear Trend
Seasonal	293.080	4926.600	1026.100	493.760
Result	Seasonal effect	Seasonal effect	Seasonal effect	Seasonal effect
CH test	1.387	1.495	1.506	1.497
Result	Stationary	Stationary	Stationary	Stationary
KPSS test	0.048	0.030	0.034	0.029
p-value	> 0.1	> 0.1	> 0.1	> 0.1
Result	Trend-stationary	Trend-stationary	Trend-stationary	Trend-stationary

Log-exchange rates	JP/EUR	US/EUR	JP/EUR	US/EUR
First difference	No	No	Yes	Yes
Linear Trend	6.556	8.240	-1.050	-0.590
Result	Linear Trend	Linear Trend	No Trend	No Trend
KPSS test	0.221	0.190	0.279	0.092
p-value	< 0.01	0.020	> 0.1	> 0.1
Result	Unit root	Unit root	Stationary	Stationary

Raining days	Cagliari	Olbia	Catania	Palermo
Linear Trend	0.067	0.236	-1.944	-0.552
Result	No Trend	No Trend	No Trend	No Trend
Seasonal	82.850	39.130	10.910	15.930
Result	Seasonal effect	Seasonal effect	Seasonal effect	Seasonal effect
CH test	1.601	1.542	1.419	1.431
Result	Stationary	Stationary	Stationary	Stationary
KPSS test	0.059	0.045	0.110	0.044
p-value	> 0.1	> 0.1	> 0.1	> 0.1
Result	Stationary	Stationary	Stationary	Stationary

Atmospheric temperatures	Cagliari	Olbia	Catania	Palermo
Linear Trend	-0.897	-0.289	-0.203	-0.449
Result	No Trend	No Trend	No Trend	No Trend
Seasonal	315.010	344.470	117.270	292.310
Result	Seasonal effect	Seasonal effect	Seasonal effect	Seasonal effect
CH test	1.470	1.562	1.563	1.401
Result	Stationary	Stationary	Stationary	Stationary
KPSS test	0.031	0.035	0.040	0.036
p-value	> 0.1	> 0.1	> 0.1	> 0.1
Result	Stationary	Stationary	Stationary	Stationary

Table 2. Optimal lag order selection according to the Akaike (AIC), Schwartz (BIC) and Hannan-Quinn (HQC) multivariate information criteria, computed from VARs of orders from 1 to 12. The symbol '*' indicates the best value of the respective information criteria.

Lags	AIC	BIC	HQC
1	-13.278	-11.128*	-12.422
2	-13.297	-10.641	-12.239
3	-13.313	-10.151	-12.054
4	-13.287	-9.619	-11.827
5	-13.307	-9.133	-11.645
6	-13.276	-8.596	-11.413
7	-13.359	-8.173	-11.295
8	-13.769	-8.077	-11.503
9	-13.652	-7.454	-11.185
10	-13.731	-7.027	-11.062
11	-14.652	-7.443	-11.782
12	-16.215*	-8.499	-13.143*

Table 3. F-tests for zero restrictions on all lags of each variable in VAR specifications 1 and 2. Tests are based on heteroskedasticity consistent standard errors.

Log-arrivals		Cagliari	Olbia	Catania	Palermo
Lags		1	1	1	1
All lags of Cagliari	F(1,55)	39.039	3.255	0.229	4.208
	p-value	[0.0000]	[0.0767]	[0.6344]	[0.0450]
All lags of Olbia	F(1,55)	0.655	23.158	0.037	0.024
	p-value	[0.4218]	[0.0000]	[0.8483]	[0.8780]
All lags of Catania	F(1,55)	2.902	0.622	36.336	0.053
	p-value	[0.0941]	[0.4338]	[0.0000]	[0.8189]
All lags of Palermo	F(1,55)	1.972	0.086	3.725	19.728
	p-value	[0.1658]	[0.7707]	[0.0588]	[0.0000]
Lags		1 and 12	1 and 12	1 and 12	1 and 12
All lags of Cagliari	F(2,51)	9.621	6.643	3.330	5.220
	p-value	[0.0003]	[0.0027]	[0.0437]	[0.0087]
All lags of Olbia	F(2,51)	1.001	9.076	0.386	0.690
	p-value	[0.3747]	[0.0004]	[0.6816]	[0.5063]
All lags of Catania	F(2,51)	3.505	0.644	20.588	2.942
	p-value	[0.0375]	[0.5293]	[0.0000]	[0.0618]
All lags of Palermo	F(2,51)	2.370	2.007	1.545	8.218
	p-value	[0.1037]	[0.1449]	[0.2231]	[0.0008]

Table 4. F-tests for zero restrictions on all lags of each variable in VAR specifications 1 and 2, and Likelihood Ratio test (the null hypothesis is that the true parameters values are equal to zero, in all equations of VAR models, for the omitted exogenous variables).

	Log-arrivals	Cagliari	Olbia	Catania	Palermo		Cagliari	Olbia	Catania	Palermo
	Lags	1	1	1	1	Lags	1 and 12	1 and 12	1 and 12	1 and 12
Log-diff. exchange rates										
Lags of Cagliari	F(1,53)	29.580	2.469	0.475	3.238	F(2,49)	8.232	4.240	2.075	3.397
	p-value	[0.0000]	[0.1221]	[0.4939]	[0.0776]	p-value	[0.0008]	[0.0200]	[0.1364]	[0.0415]
Lags of Olbia	F(1,53)	1.173	21.829	0.068	0.046	F(2,49)	1.556	8.632	0.382	0.887
	p-value	[0.2837]	[0.0000]	[0.7959]	[0.8316]	p-value	[0.2213]	[0.0006]	[0.6845]	[0.4185]
Lags of Catania	F(1,53)	5.265	0.886	37.472	0.003	F(2,49)	4.025	0.777	19.651	3.913
	p-value	[0.0258]	[0.3508]	[0.0000]	[0.9542]	p-value	[0.0241]	[0.4655]	[0.0000]	[0.0265]
Lags of Palermo	F(1,53)	3.637	0.179	3.557	17.892	F(2,49)	2.674	1.288	0.955	7.910
	p-value	[0.0619]	[0.6737]	[0.0648]	[0.0001]	p-value	[0.0790]	[0.2850]	[0.3917]	[0.0011]
Likelihood Ratio test	Chi-square(8)	13.912				Chi-square(8)	13.556			
	p-value	[0.0841]				p-value	[0.0941]			
Raining days										
Lags of Cagliari	F(1,51)	36.441	2.533	0.316	4.317	F(2,47)	7.922	5.623	2.413	4.298
	p-value	[0.0000]	[0.1177]	[0.5767]	[0.0428]	p-value	[0.0011]	[0.0065]	[0.1006]	[0.0193]
Lags of Olbia	F(1,51)	0.628	16.737	0.060	0.086	F(2,47)	1.098	7.961	0.588	1.451
	p-value	[0.4316]	[0.0002]	[0.8079]	[0.7709]	p-value	[0.3419]	[0.0011]	[0.5592]	[0.2447]
Lags of Catania	F(1,51)	4.010	0.562	41.617	0.001	F(2,47)	3.394	0.603	30.819	4.377
	p-value	[0.0506]	[0.4571]	[0.0000]	[0.9732]	p-value	[0.0420]	[0.5512]	[0.0000]	[0.0181]
Lags of Palermo	F(1,51)	1.195	0.310	3.229	15.068	F(2,47)	1.487	1.814	0.646	5.757
	p-value	[0.2795]	[0.5799]	[0.0783]	[0.0003]	p-value	[0.2366]	[0.1742]	[0.5289]	[0.0058]
Likelihood Ratio test	Chi-square(16)	21.565				Chi-square(16)	26.162			
	p-value	[0.1578]				p-value	[0.0518]			
Atmospheric temperatures										
Lags of Cagliari	F(1,51)	35.771	4.021	0.476	3.428	F(2,47)	11.541	6.347	5.254	4.607
	p-value	[0.0000]	[0.0503]	[0.4932]	[0.0699]	p-value	[0.0001]	[0.0036]	[0.0087]	[0.0149]
Lags of Olbia	F(1,51)	0.900	21.300	0.059	0.005	F(2,47)	1.258	8.370	0.600	0.609
	p-value	[0.3471]	[0.0000]	[0.8095]	[0.9454]	p-value	[0.2937]	[0.0008]	[0.5528]	[0.5480]
Lags of Catania	F(1,51)	1.806	0.003	31.370	0.002	F(2,47)	2.802	0.420	18.840	2.495
	p-value	[0.1849]	[0.9536]	[0.0000]	[0.9630]	p-value	[0.0709]	[0.6593]	[0.0000]	[0.0934]
Lags of Palermo	F(1,51)	1.948	0.000	3.121	17.128	F(2,47)	2.465	1.667	0.409	6.445
	p-value	[0.1689]	[0.9927]	[0.0833]	[0.0001]	p-value	[0.0960]	[0.1999]	[0.6669]	[0.0034]
Likelihood Ratio test	Chi-square(16)	24.530				Chi-square(16)	26.001			
	p-value	[0.0786]				p-value	[0.0540]			

Table 5. Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil's U (Theil, 1966), as measures of the overall accuracy of arrival forecasts for each airport. Forecast errors refer to the out-of-sample period January 2009-May 2009.

Forecast evaluation statistics								
Exogenous variable	None	Log-diff. exchange rates	Raining days	Atmospheric temperatures	None	Log-diff. exchange rates	Raining days	Atmospheric temperatures
Lags of endogenous variables	1	1	1	1	1 and 12	1 and 12	1 and 12	1 and 12
Endogenous variable	Log arrivals to Cagliari							
Root Mean Squared Error	0.1159	0.1261	0.1088	0.1034	0.1301	0.1282	0.1205	0.1200
Mean Abs. Percentage Error	0.8489	0.9312	0.7986	0.8162	0.8436	0.9328	0.8167	0.8139
Theil's U	0.5458	0.6114	0.5079	0.4762	0.6186	0.6157	0.5610	0.5630
# preferred model	0	0	1	2	0	0	0	0
Endogenous variable	Log arrivals to Olbia							
Root Mean Squared Error	0.1415	0.1283	0.1383	0.1172	0.2275	0.2042	0.2130	0.1831
Mean Abs. Percentage Error	1.1382	0.9032	1.0955	0.8820	1.9248	1.6604	1.7869	1.5142
Theil's U	0.4580	0.4375	0.4469	0.3777	0.7434	0.6835	0.6931	0.5944
# preferred model	0	0	0	3	0	0	0	0
Endogenous variable	Log arrivals to Catania							
Root Mean Squared Error	0.0723	0.0565	0.0953	0.0933	0.0416	0.0291	0.0603	0.0446
Mean Abs. Percentage Error	0.5109	0.3346	0.7153	0.6928	0.2675	0.1897	0.3853	0.2752
Theil's U	0.3647	0.3359	0.4784	0.4878	0.1851	0.1635	0.1974	0.1361
Preferred model	0	0	0	0	0	2	0	1
Endogenous variable	Log arrivals to Palermo							
Root Mean Squared Error	0.0416	0.0370	0.0573	0.0384	0.0363	0.0371	0.0862	0.0498
Mean Abs. Percentage Error	0.3049	0.2556	0.4450	0.2795	0.2515	0.2244	0.6557	0.3687
Theil's U	0.2149	0.2222	0.3057	0.1889	0.1630	0.2248	0.4566	0.2456
# preferred model	0	0	0	0	2	1	0	0
# preferred model total	0	0	1	5	2	3	0	1