Risk Management for Air Passenger and International Tourist Arrivals in the Balearic Islands, Spain

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Risk Management for International Tourist Arrivals:
An Application to the Balearic Islands, Spain

Abstract

Spain is a leader in terms of total international tourist arrivals and receipts. The Balearic Islands are one of the most popular destinations in Spain. For tourism management and marketing, it is essential to forecast tourist arrivals accurately. As it is important to provide sensible tourist forecast intervals, it is also necessary to model their variances accurately. Time-varying variances also provide useful information regarding the risk associated with tourist arrivals. This paper examines spatial aggregation across micro entities to more aggregated macro entities, in addition to temporal aggregation, for purposes of analyzing risk in tourism marketing and management. The paper examines four different types of asymmetric behaviour related to the effects of positive and negative shocks of equal magnitude on volatility. The paper analyzes daily air passenger arrivals from the Spanish National Airport Authority from 2001-06 to the Balearics, using time series models for the conditional mean and conditional volatility.

Keywords: Risk management, Tourism management, Tourism marketing, Daily international tourist arrivals, Time-varying volatility, Spatial aggregation, Temporal aggregation, Asymmetric behaviour.

1. Introduction

International tourism demand is important for many countries worldwide because of the tourist export receipts that they generate. Spain is one of the most visited countries in the world by international tourists, being second to France in terms of total of international tourist arrivals, and second to the USA in terms of international tourism receipts (UNWTO, 2007). Of the five major tourist regions in Spain, the Balearic Islands, comprising Mallorca, Ibiza and Menorca, are one of the most popular destinations.

It is clear that international tourist arrivals are important globally, as well as nationally for Spain. For purposes of tourism management and marketing, it is essential to be able to forecast tourist arrivals and their percentage changes accurately. As it is important to provide sensible tourist forecast intervals in addition to the forecasts themselves, it is also necessary to model the variances of the forecasts accurately. Virtually all previous empirical research in forecasting international tourist arrivals has assumed that the variance is constant. However, when the variance changes over time, it is necessary to specify the time-varying nature of the underlying process. A time-varying variance, otherwise known as time-varying volatility, also provides useful information regarding the risk (or uncertainty) associated with international tourist arrivals and their respective rates of growth. In this sense, models of international tourist arrivals, their respective percentage changes, and their associated time-varying volatilities, can make a significant contribution to tourism risk management and marketing.

Forecasting international tourism and their associated volatility has been considered previously in Chan, Lim and McAleer (2005) and Hoti, McAleer and Shareef (2007) at the multivariate level, and in Shareef and McAleer (2007) at the univariate level. These papers have shown the importance and usefulness of both univariate and multivariate conditional volatility models, when used in conjunction with time series models of international tourist arrivals and their respective rates of growth.

In the case of the Maldives, where a daily international tourist tax has been imposed, international tourists yield a significant contribution to government tax revenues. Consequently, the growth in tax revenues is equivalent to the returns in financial markets. For this reason, Shareef and McAleer (2007) examine the number and the growth in international tourist arrivals to the Maldives using financial econometric models that are used to analyze financial rates of return. This methodological approach can also be used for purposes of tourism risk management and marketing, whereby international tourist arrivals might yield relevant tax revenue.

One of the primary purposes of this paper is to extend the ideas in each of the papers above to the issue of spatial aggregation across micro entities, such as town, city, island, province, region or country, to more aggregated macro entities, such as city, island, province, region, country or continent, in addition to temporal aggregation across the seasons within a calendar year, for purposes of analyzing issues related to risk for tourism marketing and management. The effects of temporal aggregation across the seasons, as well as spatial aggregation across the three major islands in the Balearics, will be examined in connection with four different types of asymmetric behaviour that are related to the effects of positive and negative shocks of equal magnitude on volatility. One of these types of asymmetry is leverage and tourism downturn, which is derived from the related issue of leverage in financial economics. This paper introduces three other types of asymmetric behaviour, namely low season financial risk, overcrowding through overbooking and congestion, and tourism saturation. These new ideas can be applied for purposes of temporal aggregation, as well as the spatial aggregation of geographic and/or administrative entities to a more aggregated level.

The plan of the remainder of the paper is as follows. Section 2 provides an economic and tourism analysis of the Balearic Islands. Section 3 assesses the importance of using daily data to analyze passenger arrivals and the conditional variance of passenger arrivals. Section 4 examines the alternative conditional mean and conditional volatility models for daily air passenger arrivals. The estimated models and empirical results are discussed in Section 5, and some concluding remarks are given in Section 6.

2. The Balearic Islands

The Balearic Islands, Spain, with a total population of just over 1 million people (INE, 2007), are one of the leading sun and sand destinations in the Mediterranean (see Figure 1). During the year 2006 the Balearic Islands received, by air and by sea, over

12.5 million tourists, and of these, approximately 12 million arrived by plane, and 9.77 million were international tourists. The tourism industry accounts for 48% of the total GDP in the Balearics (Exceltur, 2007). However, the tourism industry is affected by seasonality, as it is in many other Mediterranean destinations. Almost 9 million tourists visited the islands between the months of May and September, but only 3.5 million visited during the remaining seven months (CITTIB, 2007). Furthermore, the local economy is not only highly dependent on tourism, but the standardized sun and sand product also predominates, despite the efforts of diversification promoted by public and private initiatives (Aguilo, Riera and Rossello, 2005).

The three main islands in the Balearics are Mallorca, Ibiza and Menorca (for purposes of simplicity, data for the small island of Formentera is integrated with Ibiza), and each has an international airport in their respective capital cities of Palma de Mallorca, Ibiza and Mahon. Although all the islands enjoy the same climate, there are differences in their economic structures, the number of tourist arrivals, seasonal patterns, and the profiles of tourists who visit each island. Mallorca accounts for 79% of Balearic regional GDP, while Menorca and Ibiza represent 9% and 12%, respectively (CAIB, 2004). In Mallorca, total demand from tourism corresponds to 34% of island GDP, in Ibiza this percentage is 44%, and in Menorca tourism demand represents 28% of island GDP (CAIB, 2004).

In 2006, Mallorca received a total of 9.6 million tourists. Of these, 38.4% were from Germany and 24.2% from the United Kingdom (see Table 1). In comparison, Ibiza, with 1.87 million visitors, had 35.2% from Britain, 17.1% from Germany and 14.8% from Italy. For Menorca, the British represented 50.3% of tourists, followed by domestic tourism (29.4%) of a total of 1.009 million tourist arrivals in 2006 (CITTIB, 2007). It is worth noting that Menorca and Ibiza suffer greater seasonality than does Mallorca. In 2005, 57.8% of the total tourist arrivals in Mallorca stayed during the high season, whereas in Menorca and Ibiza, this figure was as high as 83% (CRE, 2005).

These figures give an idea of the existing differences among the three islands. Moreover, the image promoted by each island is different. While Menorca appeals primarily to families, Ibiza attracts a younger market, and Mallorca receives a broader array of tourist segments. As a consequence, the majority of tourists in Menorca enjoy day time activities, the Ibiza visitors are more interested in the night life, while in Mallorca both, day and night activities, are sought (CITTIB, 2007). These differences suggest that each island should be considered as a different tourism destination for purposes of tourism planning, management and promotion.

Due to the importance of tourism in the Balearics, many researchers have used this destination to analyze different aspects of tourism. In particular, from the demand perspective, Aguilo et al (2005) and Garin and Montero (2007) estimated price and income elasticities using yearly passenger arrivals data. From a microeconomic perspective, Alegre and Pou (2006) demonstrated the trend of tourists staying for shorter periods. However, it has also been shown that the islands benefit from a high repeat visitation rate (Alegre and Cladera, 2006; Garin and Montero, 2007).

On the supply side, it has been recognized that the islands have reached their maximum carrying capacity, as well as the importance of protecting the natural environment and preserving the local cultural identity (Bujosa and Rossello, 2007; Knowles and Curtis, 1999). The role of tour operators in the commercialization and price structure of the packaged sun and sand product has also been investigated, arriving at the conclusion that British and German tour operators have an oligopolistic position towards accommodation providers and customers (Aguilo, Alegre and Riera, 2001).

This paper analyzes daily air passenger arrivals between 2001 and 2006 to the three international airports, giving a total of 2,191 observations for each island. Daily passenger arrivals data are obtained from the Spanish National Airport Authority (AENA). As data on daily tourist arrivals are not available, total passenger arrivals data are used as a proxy. Figure 2 shows the monthly international tourist arrivals and monthly air passenger arrivals. As the correlation coefficient between these two monthly series is 0.997, it is highly likely that daily passenger arrivals data would be an accurate proxy for daily international tourist arrivals.

3. Data

The data set comprises daily passenger arrivals at the three international airports in the Balearic Islands, namely Palma de Mallorca, Ibiza and Mahon, which are located in the islands of Mallorca, Ibiza and Menorca, respectively, with data for the Balearics being the aggregate of arrivals to the three islands. The data are daily, for the period 1 January 2001 to 31 December 2006, giving a total of 2,191 observations. The source of data is the AENA (Aeropuertos Españoles y Navegación Aérea), the Spanish National Airport Authority.

The importance of using daily air passenger arrivals cannot be ignored. As compared with the use of aggregated data, daily data provide more detailed information, so that estimation will be more precise for purposes of modeling and forecasting international tourist arrivals. Furthermore, daily data are very useful for purposes of modeling the conditional variance of the time series when the assumption of constant variances is deemed to be unreasonable.

Figure 3 plots the daily air passenger arrivals for Mallorca, Menorca, Ibiza and the Balearics. Figure 4 plots the volatility of daily air passenger arrivals, where volatility is defined as the squared deviation from the sample mean.

Tourism seasonality is clear in all three islands, and there seems to be an increasing number of arrivals during the winter months, especially for Mallorca. However, in Menorca the number of passenger arrivals during the summer months appears to be decreasing. Another common pattern found in the arrivals to the three islands is how they decrease dramatically at the end of October. There is a single observation in summer 2002, which is a consequence of the one-day general strike called by the Spanish trade unions in protest at the proposed changes to unemployment benefits. This observation is clearly seen in the Palma de Mallorca sample, where arrivals were kept to a legally prescribed minimum for all three islands. Clearly, this affected Mallorca far more severely than it did to Ibiza or Menorca. There are peaks for the Christmas holidays in Palma de Mallorca during the low season, which is hardly noticeable in the other two islands. Nevertheless, the behaviour of the volatility of arrivals appears to be very similar between the islands, having higher volatility during the high season and lower volatility during the low season.

Figures 5 and 6 plot the weekly differences and the volatility, respectively, in daily air passenger arrivals for the four samples. A closer analysis of Figures 3 and 4 shows a weekly pattern in the data. Consequently, the weekly difference in passenger arrivals in Figure 5 and its volatility in Figure 6 seem to have eliminated the weekly pattern.

Table 2 gives the descriptive statistics of air passenger arrivals for the four samples. Palma Airport receives the majority of passengers who visit the Balearics. The third and fourth standardized moments about the mean, skewness and kurtosis, respectively, are also presented. Skewness (μ_3/σ^3) is a measure of asymmetry of the distribution of the series around its mean. Kurtosis (μ_4/σ^4) is a measure of peakedness, such that higher kurtosis means more of the variability is due to infrequent extreme deviations. The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

The Jarque-Bera Lagrange multiplier test examines whether the series are normally distributed. The test statistic measures the difference in the skewness and kurtosis of the empirical series from those under the normal distribution. Under the null hypothesis of normality, the Jarque-Bera test statistic is distributed as chi-squared with 2 degrees of freedom. The reported "Prob." is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis. All four samples are found to be not normally distributed.

Table 3 gives the descriptive statistics of the weekly difference in air passenger arrivals for the four samples. The median is considerably greater than the mean in all four data sets. The distribution of air passenger arrivals in negatively skewed for Palma and the Balearics, but is positively skewed for Ibiza and Mahon. The Jarque-Bera Lagrange multiplier test of normality suggests that all four samples are not normally distributed.

4. Conditional Mean and Conditional Volatility Models

The alternative time series models to be estimated for the conditional means of the daily air passenger arrivals and weekly changes in passenger arrivals, as well as their conditional volatilities, are discussed below. As Figures 3 to 6 illustrate, daily air passenger arrivals, and the weekly change in daily passenger arrivals to the Balearics, show periods of high volatility followed by others of relatively low volatility. One implication of this persistent volatility behaviour is that the assumption of (conditionally) homoskedastic residuals is inappropriate (see, for example, Li, Ling and McAleer (2002), and McAleer (2005)).

For a wide range of financial data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model, which was proposed by Engle (1982). When the time-varying conditional variance has both autoregressive and moving average components, this leads to the generalized ARCH(*p,q*), or GARCH(*p,q*), model of Bollerslev (1986). The lag structure of the appropriate GARCH model can be chosen by information criteria, such as those of Akaike and Schwarz, although it is very common to impose the widely estimated GARCH(1,1) specification in advance.

Consider the stationary AR(1)-GARCH(1,1) model for daily air passenger arrivals to the Balearics (or their weekly change, as appropriate), y_t:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t, \qquad |\phi_1| < 1 \tag{1}$$

for $t = 1,...,n$, where the shocks (or movements in daily air passenger arrivals) are given by:

$$\begin{aligned} \varepsilon_t &= \eta_t \sqrt{h_t}, \quad \eta_t \sim iid(0,1) \\ h_t &= \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{2}$$

where $\omega > 0, \alpha \geq 0$ and $\beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The AR(1) model in equation (1) can easily be extended to univariate or multivariate ARMA(*p,q*) processes (for further details, see Ling and McAleer (2003a)). In equation (2), the ARCH (or α) effect indicates the short run persistence of shocks, while the GARCH (or β) effect indicates the contribution of shocks to long run persistence (namely, $\alpha + \beta$). The stationary AR(1)-GARCH(1,1) model can be modified to incorporate a non-stationary ARMA(*p,q*) conditional mean and a stationary GARCH(*r,s*) conditional variance, as in Ling and McAleer (2003b).

In equations (1) and (2), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t. The conditional log-likelihood function is given as follows:

$$\sum_{t=1}^{n} l_t = -\frac{1}{2}\sum_{t=1}^{n}\left(\log h_t + \frac{\varepsilon_t^2}{h_t}\right).$$

The QMLE is efficient only if η_t is normal, in which case it is the MLE. When η_t is not normal, adaptive estimation can be used to obtain efficient estimators, although this can be computationally intensive. Ling and McAleer (2003b) investigate the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH(*r,s*) errors.

Ling and McAleer (2003a) showed that the QMLE for GARCH(*p,q*) is consistent if the second moment of ε_t is finite. For GARCH(*p,q*), Ling and Li (1997) demonstrated that the local QMLE is asymptotically normal if the fourth moment of ε_t is finite, while Ling and McAleer (2003a) proved that the global QMLE is asymptotically normal if the sixth moment of ε_t is finite. Using results from Ling and Li (1997) and Ling and McAleer (2002a; 2002b), the necessary and sufficient condition for the existence of the second moment of ε_t for GARCH(1,1) is $\alpha + \beta < 1$ and, under normality, the necessary and sufficient condition for the existence of the fourth moment is $(\alpha+\beta)^2 + 2\alpha^2 < 1$.

As discussed in McAleer, Chan and Marinova (2007), Elie and Jeantheau (1995) and Jeantheau (1998) established that the log-moment condition was sufficient for consistency of the QMLE of an univariate GARCH(p,q) process (see Lee and Hansen (1994) for the proof in the case of GARCH(1,1)), and Boussama (2000) showed that the log-moment condition was sufficient for asymptotic normality. Based on these theoretical developments, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition, namely

$$E(\log(\alpha\eta_t^2 + \beta)) < 0. \qquad (3)$$

This condition involves the expectation of a function of a random variable and unknown parameters. Although the sufficient moment conditions for consistency and asymptotic normality of the QMLE for the univariate GARCH(1,1) model are stronger than their log-moment counterparts, the second moment condition is more straightforward to check in practice.

The effects of positive shocks (or upward movements) on the conditional variance, h_t, are assumed to be the same as the negative shocks (or downward movements) in the symmetric GARCH model. In order to accommodate asymmetric behavior, Glosten, Jagannathan and Runkle (1992) proposed the GJR model, for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \qquad (4)$$

where $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0$ and $\beta \geq 0$ are sufficient conditions for $h_t > 0$, and $I(\eta_t)$ is an indicator variable defined by:

$$I(\eta_t) = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \varepsilon_t \geq 0 \end{cases}$$

as η_t has the same sign as ε_t. The indicator variable differentiates between positive and negative shocks of equal magnitude, so that asymmetric effects in the data are captured by the coefficient γ, with $\gamma \geq 0$. The asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \frac{\gamma}{2}$, and to long run persistence, $\alpha + \beta + \frac{\gamma}{2}$.

Ling and McAleer (2002b) showed that the regularity condition for the existence of the second moment for GJR(1,1) under symmetry of η_t is given by:

$$\alpha+\beta+\frac{1}{2}\gamma<1, \tag{5}$$

while McAleer et al. (2007) showed that the weaker log-moment condition for GJR(1,1) was given by:

$$E(\log[(\alpha+\gamma I(\eta_t))\eta_t^2+\beta])<0, \tag{6}$$

which involves the expectation of a function of a random variable and unknown parameters.

An alternative model to capture asymmetric behavior in the conditional variance is the Exponential GARCH (EGARCH(1,1)) model of Nelson (1991), namely:

$$\log h_t=\omega+\alpha\,|\,\eta_{t-1}\,|+\gamma\eta_{t-1}+\beta\log h_{t-1}, \quad |\,\beta\,|<1 \tag{7}$$

where the parameters have a distinctly different interpretation from those in the GARCH(1,1) and GJR(1,1) models.

As noted in McAleer et al. (2007), there are some important differences between EGARCH and the previous two models, as follows: (i) EGARCH is a model of the logarithm of the conditional variance, which implies that no restrictions on the parameters are required to ensure $h_t>0$; (ii) Shephard (1996) observed that $|\,\beta\,|<1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iii) as the conditional (or standardized) shocks appear in equation (7), $|\,\beta\,|<1$ would seem to be a sufficient condition for the existence of moments; (iv) in addition to being a sufficient condition for consistency, $|\,\beta\,|<1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

Furthermore, EGARCH captures asymmetries differently from GJR. The parameters α and γ in EGARCH(1,1) represent the magnitude (or size) and sign effects of the conditional (or standardized) shocks, respectively, on the conditional variance, whereas α and $\alpha+\gamma$ represent the effects of positive and negative shocks, respectively, on the conditional variance in GJR(1,1).

The following is an interpretation of asymmetries in EGARCH(1,1) for air passenger arrivals. Depending on the negative or positive slopes according to a positive or negative shock (see Figures 7 to 10), there are four possible scenarios of asymmetry in the EGARCH model, according to the restrictions on α and γ, as follows:

(i) Type 1 Asymmetry: Low Season Financial Risk, in which negative shocks increase volatility and positive shocks of a similar magnitude increase volatility by a smaller amount.

(ii) Type 2 Asymmetry: Overbooking Pressure on Carrying Capacity, in which negative shocks increase volatility and positive shocks of a similar magnitude increase volatility by a larger amount.

(iii) Type 3 Asymmetry: Tourism Saturation in High Season, in which negative shocks decrease volatility and positive shocks of a similar magnitude increase volatility.

(iv) Type 4 Asymmetry: Leverage and Tourism Downturn, in which negative shocks increase volatility and positive shocks of a similar magnitude decrease volatility.

5. Estimated Models

It is well known that traditional unit root tests, primarily those based on the classic methods of Dickey and Fuller (1979; 1981) and Phillips and Perron (1988), suffer from low power and size distortions. However, these shortcomings have been overcome by various modifications to the testing procedures, such as the methods proposed by Perron and Ng (1996), Elliott, Rothenberg and Stock (1996), and Ng and Perron (2001).

We have applied the modified unit root tests, denoted as $MADF^{GLS}$ and MPP^{GLS}, to the time series of daily passenger arrivals in the Balearics, and to the three sub-samples of Mallorca, Menorca and Ibiza. In essence, these tests use GLS de-trended data and the modified Akaike information criterion (MAIC) to select the optimal truncation lag. The asymptotic critical values for both tests are given in Ng and Perron (2001).

The results of the unit root tests are obtained from the econometric software package EViews 5.0, and are reported in Tables 4, 5, 6 and 7. The existence of a zero frequency unit root is tested for the arrivals as well as weekly differences (that is, the seven day differences) for the three islands and the total of the Balearics.

In Tables 4-7, the lags are all in the order of 20 to 25 days, which is roughly three weeks of daily data. In Table 1 for the Balearics, the existence of a unit root is rejected by both tests and for both passenger arrivals and the weekly difference in passenger arrivals, regardless of whether both tests have an intercept only or both an intercept and deterministic trend. The results are virtually identical, both quantitatively and qualitatively, for Ibiza, Menorca and Mallorca in Tables 5-7, respectively.

In short, the variable that is of primary interest for tourism management and marketing, namely passenger arrivals, is found to be stationary for each of the three major islands, as well as the Balearics. It follows, therefore, that the weekly difference is also stationary. However, as the weekly differences exhibit a different pattern from the passenger arrivals series, we will estimate models for both series, as well as their respective volatilities.

The following models are used to estimate passenger arrivals (Models 1 and 3) and the weekly differences in passenger arrivals (Models 2 and 4), as well as their respective volatilities using GARCH(1,1), GJR(1,1) and EGARCH(1,1):

Model 1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

Model 2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

Model 3: $y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$

Model 4: $\Delta_7 y_t = \phi_0 + \phi_1 \delta_H \Delta_7 y_{t-1} + \phi_2 \delta_L \Delta_7 y_{t-7} + \varepsilon_t$

where the dummy variables δ_H and δ_L distinguish between the high and low tourist seasons in all four data sets, and are defined as follows:

$\delta_H = 1$ ($\delta_L = 0$) for the high tourist season, 1 April to 31 October;

$\delta_H = 0$ ($\delta_L = 1$) for the low tourist season, 1 November to 31 March.

Model 1 explains daily passenger arrivals to one destination as depending on passenger arrivals lagged 1 and 7 days, while Model 3 distinguishes between the high and low seasons in terms of explaining daily passenger arrivals. Model 2 explains the weekly differences in passenger arrivals as an autoregressive process of order 1, and Model 4 explains the change in weekly passenger arrivals as a restricted autoregressive process of order 7.

Models 3 and 4 enable an investigation of the differences between the high and low tourist seasons in terms of forecasting daily passenger arrivals and weekly differences in passenger arrivals. In addition to the issue of aggregation across the three islands to obtain total passenger arrivals for the Balearic Islands, an examination of passenger arrival patterns across the high and low seasons, as well as their associated volatilities, will be able to provide more useful information for purposes of tourism management and marketing.

The conditional means and conditional volatilities of passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca are given for Model 1 in Tables 8-11, respectively. In each table, the estimates are given for the conditional mean that are estimated simultaneously with the estimates of the corresponding conditional volatility model. The second moment and log-moment conditions are also given for the GARCH and GJR models. The maximized log likelihood values are also given for three models for each of the four data sets. These will be used for purposes of the likelihood ratio tests of the constancy of the coefficients in the high and low seasons, to be discussed in Table 24 below.

It is striking that the results in Tables 8-11 are qualitatively very similar. The estimates of the conditional means are numerically and statistically adequate, with ϕ_1 in all cases being numerically small but statistically significant, the estimates for Ibiza being the largest in the range (0.065, 0.069), and the estimates of ϕ_2 being in excess of 0.933 in all cases.

The estimates of the conditional volatilities in each case are also numerically and statistically adequate. It is clear that the assumption of a constant variance is untenable as compared with time-varying volatility. In Table 8 for the Balearic Islands, the second moment condition for GARCH(1,1) is not satisfied but the log-moment condition is satisfied, so that the QMLE are consistent and asymptotically normal, and can hence be used to draw valid inferences. As compared with standard financial econometric models, the short run persistence of shocks, α, is quite large at 0.6, whereas the contribution of lagged conditional volatility, β, is relatively small at around 0.42. Similar comments also apply to the GJR(1,1) model, where the asymmetry coefficient, γ, is zero, so that there is no asymmetric effect of positive and negative shocks of equal magnitude on volatility. The EGARCH(1,1) estimates also suggest symmetry between negative and positive shocks of equal magnitude as the estimate of γ is also not statistically significant. Overall the GARCH(1,1) and EGARCH(1,1,) are statistically and numerically sound.

Tables 9-11 give the estimates for Model 1 for Ibiza, Menorca and Mallorca, respectively. Overall, the results in these three tables are qualitatively similar to those in Table 8 for the Balearics. In particular, the results for the conditional mean are quite similar for all three islands and the Balearics. The conditional volatility estimates are also reasonably similar for all three islands. The asymmetry coefficients in both GJR and EGARCH are insignificant in all cases, such that the effects on volatility of positive and negative shocks of similar magnitude are symmetric. The effect of lagged volatility, β, for all three islands is considerably larger than for the Balearics, while the short run persistence of shocks for Mallorca is considerably lower than the counterparts for the Balearics. In spite of the second moment condition not being satisfied for GARCH or GJR for any of the three islands, the log-moment condition is satisfied in all cases.

Therefore, the QMLE are consistent and asymptotically normal, and inferences are valid.

The conditional means and conditional volatilities of the weekly change in passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca are given for Model 2 in Tables 12-15, respectively. In Table 12 for the Balearic Islands, the effect of the lagged weekly change in passenger arrivals is highly significant at around 0.72, whereas the effects are much lower at around 0.6, 0.57 and 0.62 for Ibiza, Menorca and Mallorca in Tables 13-15, respectively. For the conditional volatility models, the estimated asymmetric effect, γ, is significant for the Balearic Islands, but not for Ibiza, Menorca or Mallorca, such that GJR is preferred to GARCH in only one of four cases. However, the asymmetry coefficient is insignificant in all four cases for the EGARCH model. The second moment condition is satisfied for the Balearic Islands and Mallorca, but the log-moment condition is satisfied in all four cases. Therefore, the QMLE are consistent and asymptotically normal, and inferences are valid.

Tables 16-19 give the conditional means and conditional volatilities of the daily passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca, respectively, for Model 3. The results are qualitatively similar for all four data sets. The differences between the high and low seasons are significant for all four data sets and all three models, particularly for Ibiza and Menorca. It is striking that the effect of lagged weekly passenger arrivals is much lower for Ibiza and Menorca in the low season as compared with the high season, whereas this is not the case for Mallorca and the Balearic Islands. The asymmetry coefficient is insignificant for GJR and EGARCH, so that positive and negative shocks of equal magnitude have a similar effect on volatility. The short run persistence of shocks for the GARCH model are 0.614, 0.612, 0.683, and a considerably lower 0.428 for the Balearics, Ibiza, Menorca and Mallorca, respectively. In spite of the second moment condition not being satisfied for GARCH or GJR for any of the four data sets, the log-moment condition is satisfied in all cases. Therefore, the QMLE are consistent and asymptotically normal, and inferences are valid.

The conditional means and conditional volatilities of the weekly change in passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca are given for Model 4 in Tables 20-23, respectively. For the conditional mean of the weekly change in passenger arrivals, there is a clear difference between the effect of the lagged change in weekly passenger arrivals between the high and low tourist seasons, with the high season effect being much greater than its low season counterpart, especially for Ibiza and Menorca. For the conditional volatility models, the asymmetric effect is significant for EGARCH for Ibiza and Menorca, but not for the Balearic Islands and Mallorca. Moreover, the asymmetry coefficient is significant for GJR for the Balearics, Ibiza and Menorca, but not Mallorca. It is striking that the asymmetric effects of positive and negative shocks of equal magnitude on volatility are significant for both GJR and EGARCH for Ibiza and Menorca. Although the second moment condition is not satisfied for Ibiza or Menorca, the log-moment condition is satisfied in all four cases. Therefore, the QMLE are consistent and asymptotically normal, and inferences are valid.

For purposes of analyzing whether asymmetry in the EGARCH model is of Type 1, 2, 3 or 4, it is necessary to check that the asymmetry coefficient, γ, is different from zero. The estimates of γ for EGARCH in Models 1, 2 and 3 are not statistically significant in any of the four data sets. However, the asymmetry coefficient is positive and statistically significant in Model 4 for Ibiza and Menorca (see Tables 21 and 22, respectively). Moreover, the estimates of the size effect, α, are positive and significant, and much greater than the corresponding estimates of γ. Therefore, the volatility for Ibiza and Menorca exhibit Type 2 Asymmetry, namely overbooking pressure on carrying capacity.

Table 24 gives the likelihood ratio test of constancy of coefficients in the high and low seasons. The first set of results relates to Model 1 as the null hypothesis and Model 3 as the alternative, whereas the second set of results has Model 2 as the null hypothesis and Model 4 as the alternative. Apart from non-rejection of Model 1 as the null hypothesis using GARCH and GJR for the Balearics, and non-rejection of Model 2 as the null hypothesis using EGARCH for Mallorca, every other set of results rejects the constancy of coefficients in the high and low seasons for all data sets and for all conditional volatility models. Therefore, there is a clear difference between the impact of lagged effects in explaining passenger arrivals and the weekly difference in passenger arrivals in the high and low tourist seasons.

6. Concluding Remarks

International tourism generates significant tourist export receipts worldwide. Crucial information required for optimal decision making in terms of planning, managing and promotion related to tourism, is an accurate forecast of international tourist arrivals, changes in tourist arrivals, and associated forecast intervals. In this respect, time-varying variances, otherwise known as time-varying volatility, provide useful information regarding the risk (or uncertainty) associated with international tourist arrivals.

There are several practical applications in which accurate forecasts of international tourist arrivals, and their associated forecast intervals, would be useful. For example, where a daily international tourist tax might be levied, the number of international tourist arrivals would yield a significant contribution to government tax revenues, such that the growth in tax revenues would be equivalent to returns in financial markets. Such returns can be analyzed using financial econometric models. This methodological approach can also be used for purposes of tourism risk management and marketing, whereby international tourist arrivals yield relevant tax revenue.

One of the primary purposes of this paper was to examine spatial aggregation across micro entities, such as town, city, island, province, region or country, to more aggregated macro entities, such as city, island, province, region, country or continent, in addition to temporal aggregation across the high and low seasons within a calendar year, for purposes of analyzing risk in tourism marketing and management. The paper examined four different types of asymmetric behaviour related to the effects of positive and negative shocks of equal magnitude on volatility. One of these types of asymmetry was leverage and tourism downturn, which is derived from the concept of leverage in financial economics. The paper also developed three other types of asymmetric behaviour, namely low season financial risk, overcrowding through overbooking and congestion, and tourism saturation. These new ideas can be applied to temporal aggregation, as well as the spatial aggregation of geographic and/or administrative entities to a more aggregated level.

Spain is a world leader in terms of total international tourist arrivals and international tourism receipts. Of the five major tourist regions in Spain, the Balearic Islands of Mallorca, Ibiza and Menorca are one of the most popular destinations. This paper analyzed daily passenger arrivals to the three international airports in the Balearic Islands, namely Palma de Mallorca (in Mallorca), Ibiza (in Ibiza), and Mahon (in Menorca), using time series models for the conditional mean and three widely used conditional volatility models for the time-varying risk. The three conditional volatility models, GARCH, GJR and EGARCH, included two models that accommodated the asymmetric effects of positive and negative shocks of equal magnitude in passenger arrivals on volatility. Daily passenger arrivals data for the period 1 January 2001 to 31 December 2006 provided a total of 2,191 observations. The source of data was the AENA (Aeropuertos Españoles y Navegación Aérea), the Spanish National Airport Authority.

The variable that is of primary interest for tourism management and marketing, namely passenger arrivals, was found to be stationary for each of the three islands, as well as for the Balearics. As the weekly differences in passenger arrivals exhibited a different pattern from the daily arrivals data, both time series, as well as their respective volatilities, were modelled for the four different data sets.

Alternative lag structures were used to model passenger arrivals and their weekly changes, as well as the differences between the high and low tourist seasons in terms of forecasting daily passenger arrivals. The empirical results indicated significant differences in the estimates of passenger arrivals at the island and aggregated levels, as well as in their associated volatilities. Moreover, the likelihood ratio test of constancy of coefficients in the high and low seasons indicated clear differences between the impact of lagged effects in explaining passenger arrivals and the weekly difference in passenger arrivals in the high and low tourist seasons.

These empirical results suggest that the new ideas developed in the paper can be useful for analyzing temporal aggregation, as well as the spatial aggregation of geographic and/or administrative entities to a more aggregated level. These findings should be relevant for tourism planning, tourism policy design and tourism management at all levels of government decision making.

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Figure 1. Map of the Balearic Islands

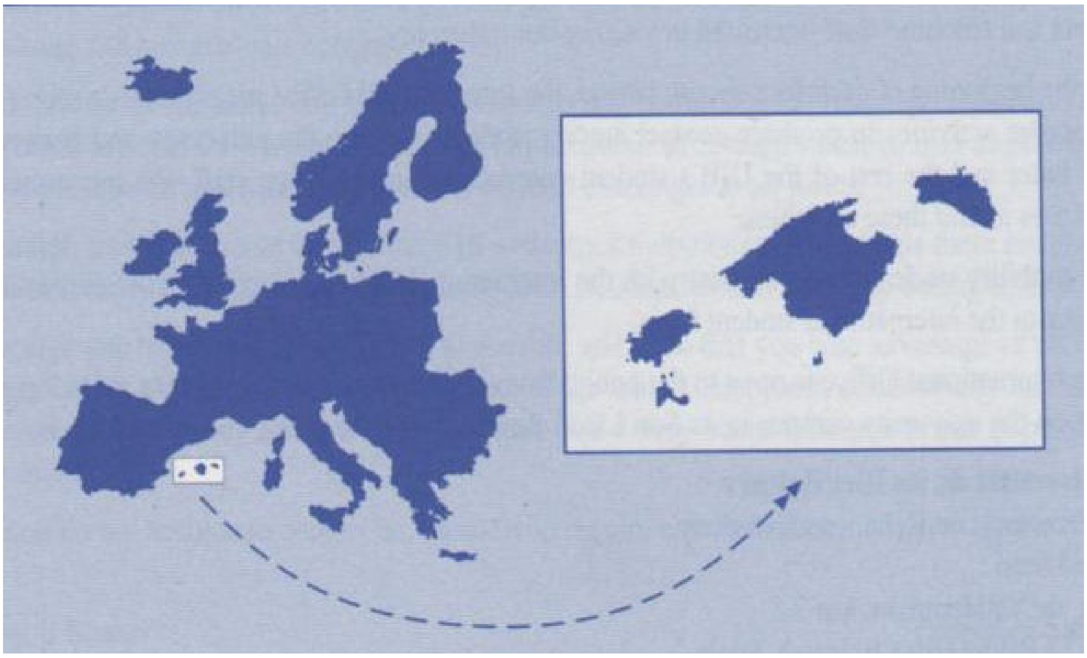


Figure 2. International Tourist and Passenger Arrivals

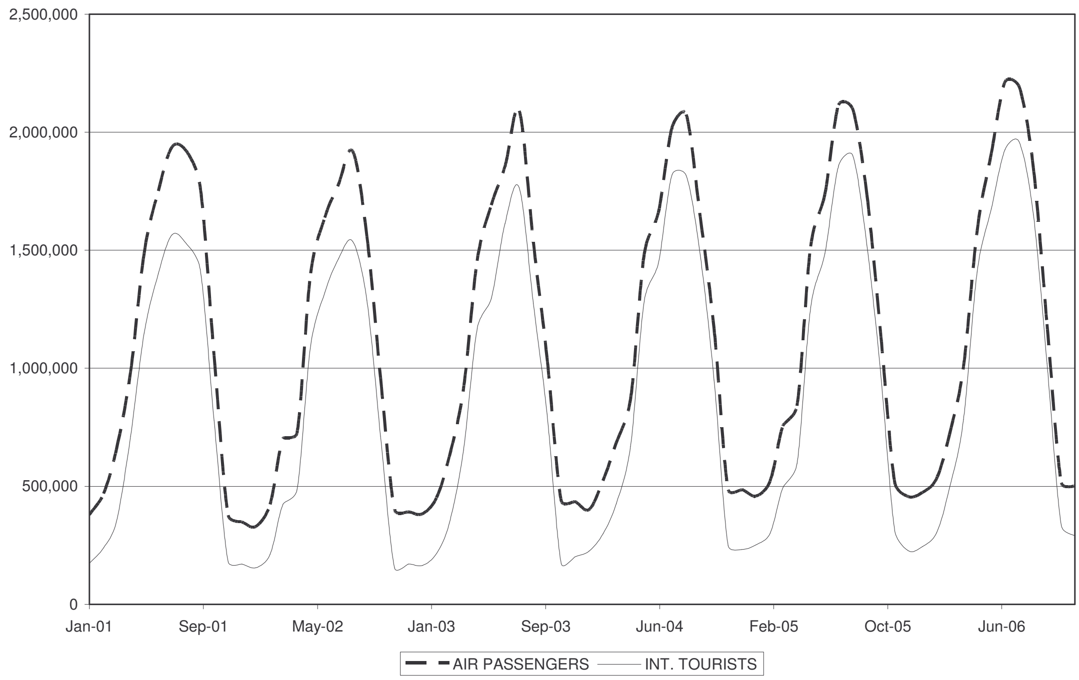


Figure 3. Daily Passenger Arrivals

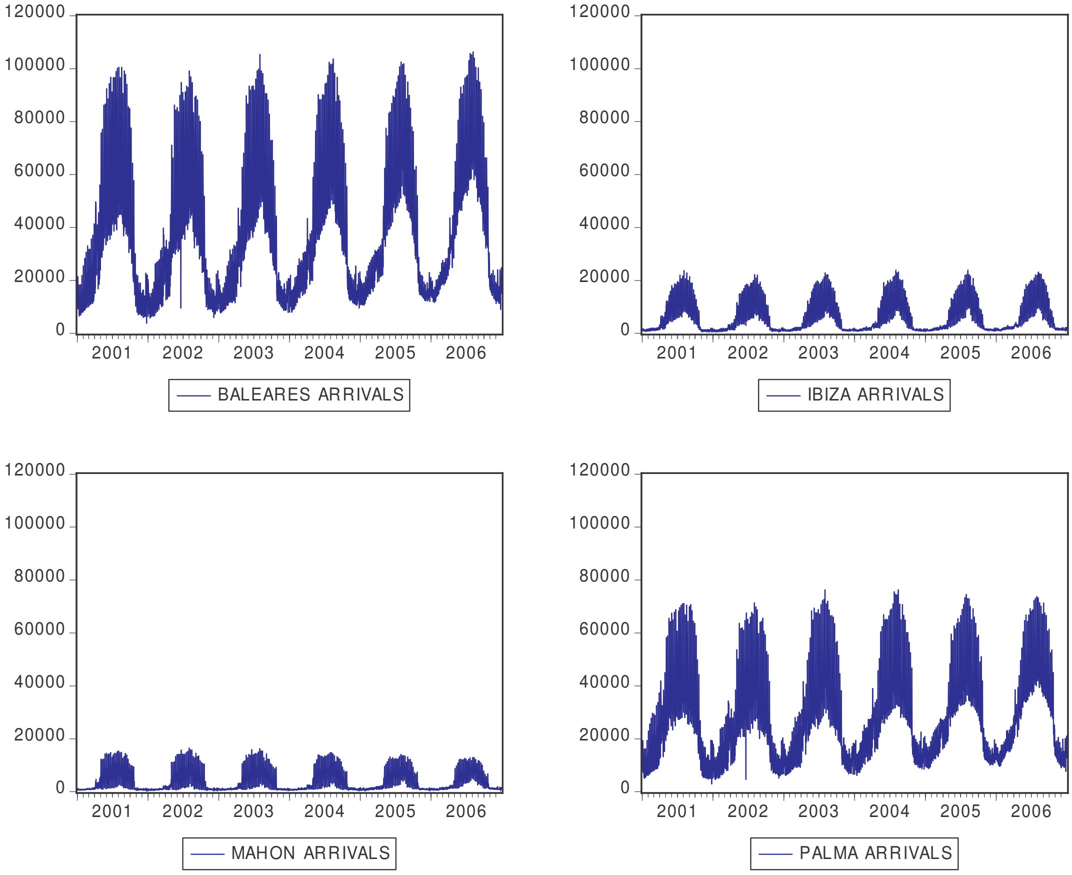


Figure 4. Volatility of Passenger Arrivals

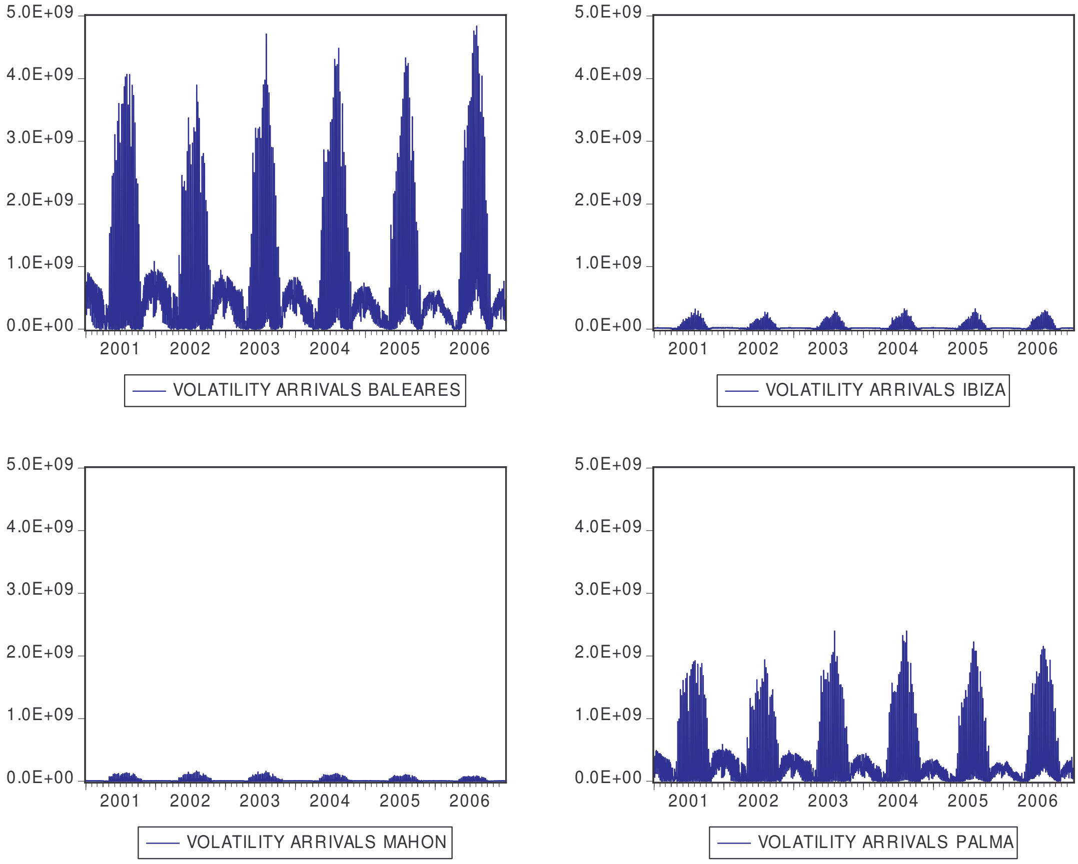
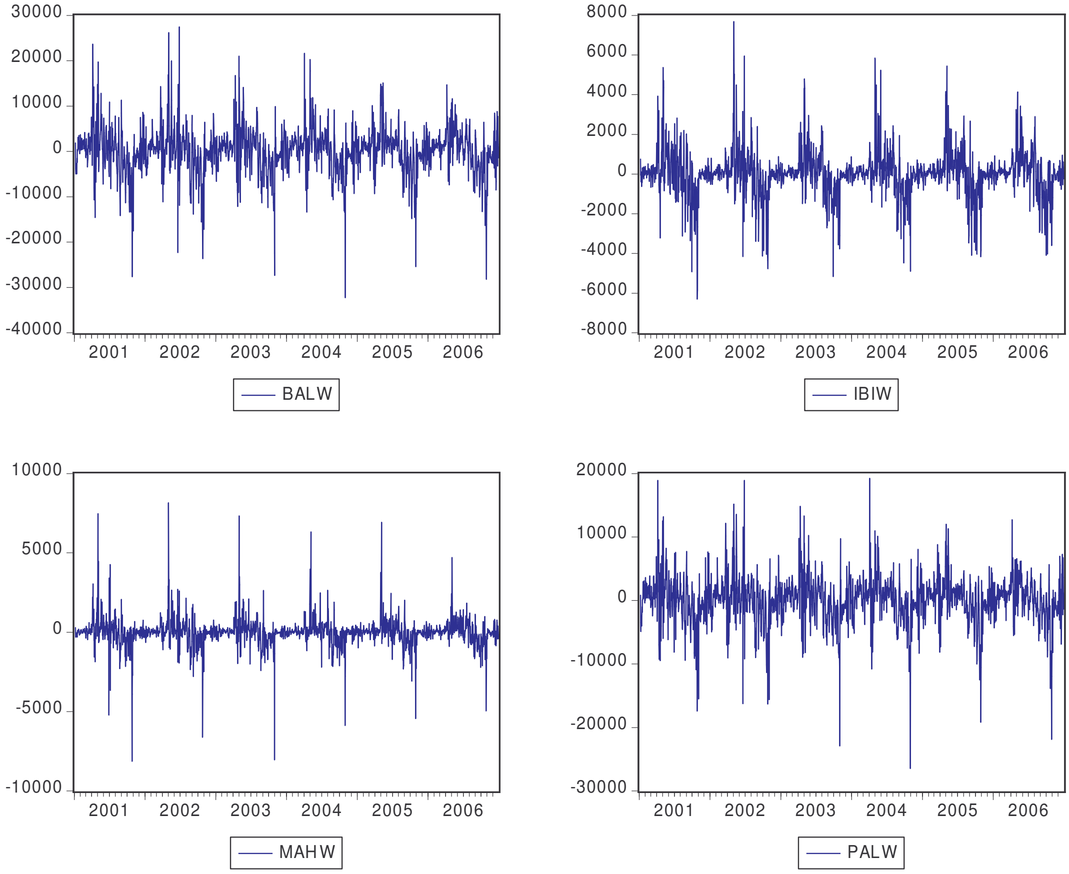
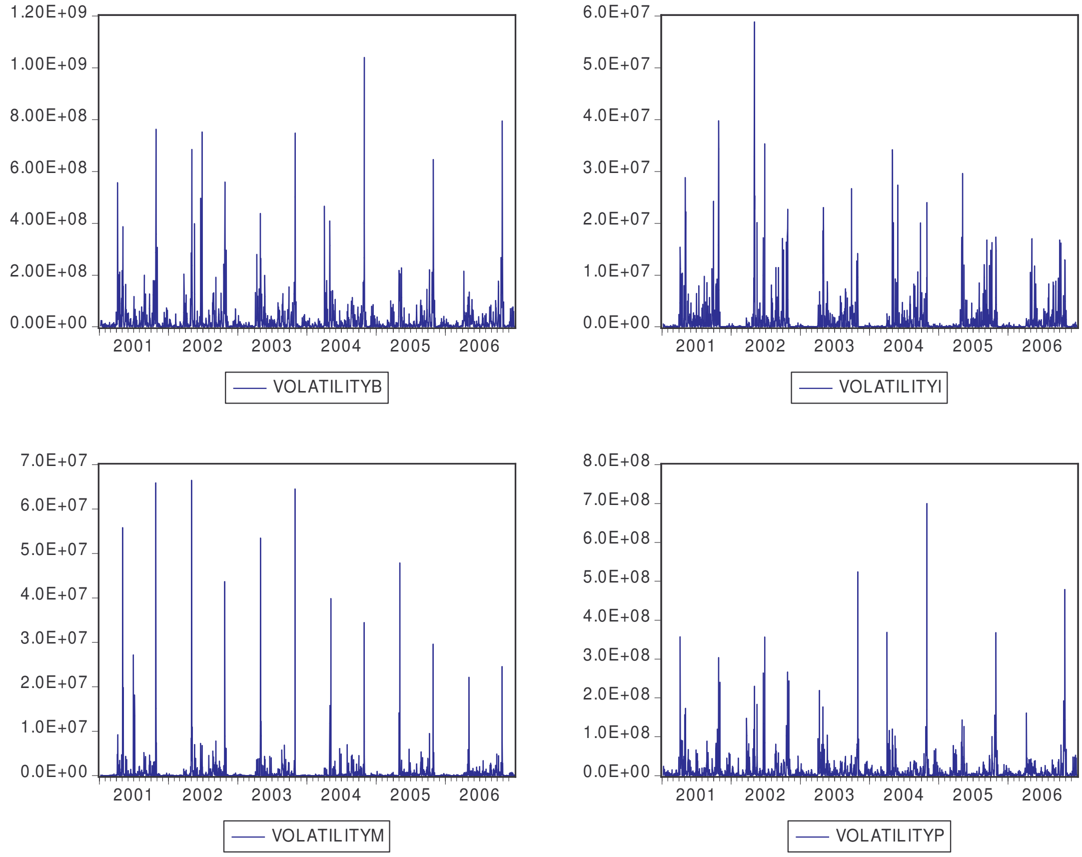


Figure 5. Weekly Difference in Passenger Arrivals



Notes:
"BALW" is the Balearic weekly difference.
"IBIW" is the Ibiza weekly difference
"MAHW" is the Mahon weekly difference
"PALW" is the Palma weekly difference

Figure 6. Volatility of Weekly Difference in Passenger Arrivals



Notes:
"VOLATILITYB" is the volatility of the Balearic weekly difference.
"VOLATILITYI" is the volatility of the Ibiza weekly difference.
"VOLATILITYM" is the volatility of the Mahon weekly difference.
"VOLATILITYP" is the volatility of the Palma weekly difference.

Figure 7. Type 1 Asymmetry: Low Season Financial Risk

($\alpha > 0$, $-\alpha < \gamma < 0$)

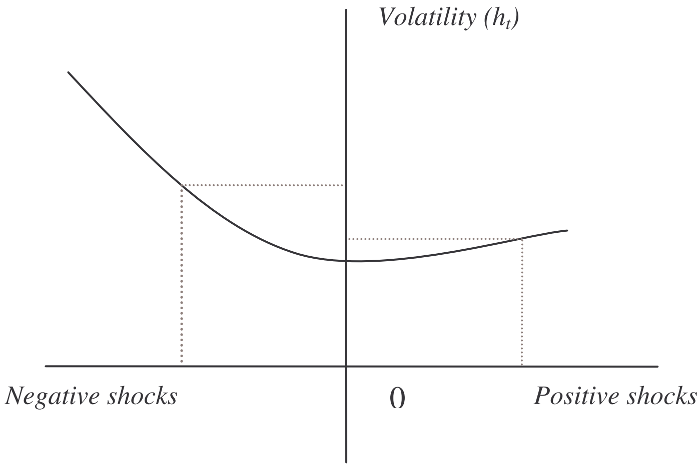


Figure 8. Type 2 Asymmetry: Overbooking Pressure on Carrying Capacity

($\alpha > 0$, $0 < \gamma < \alpha$)

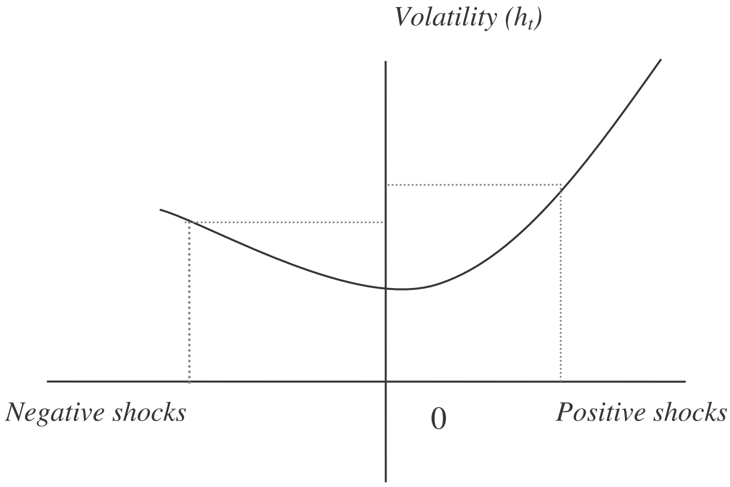


Figure 9. Type 3 Asymmetry: Tourism Saturation in High Season

($\gamma > 0$, $-\gamma < \alpha < \gamma$)

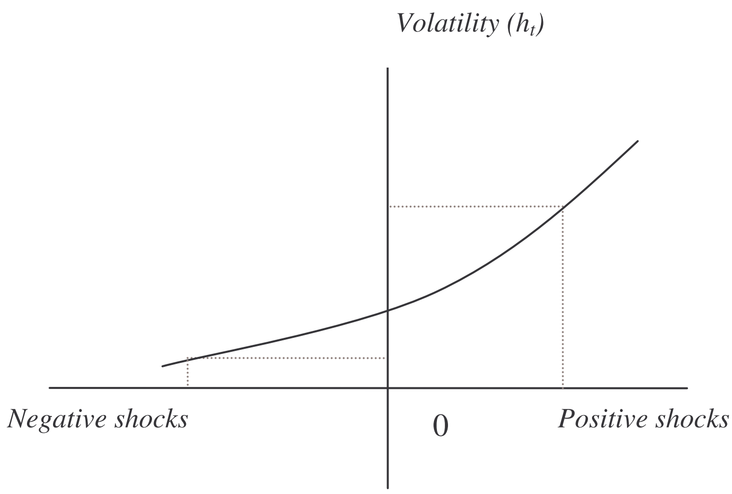


Figure 10. Type 4 Asymmetry: Leverage and Tourism Downturn

($\gamma < 0$, $\gamma < \alpha < -\gamma$)

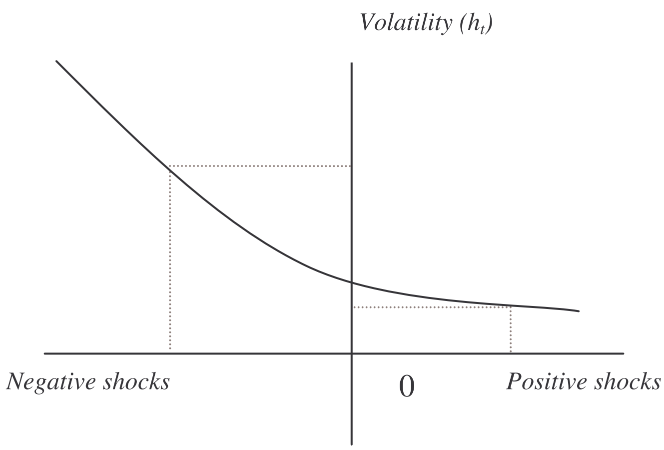


Table 1. Air Tourist Arrivals to Balearics and Main Countries of Origin, 2006

Islands	Tourist Arrivals (millions)	Germans %	British %	Italians %	Domestic %
Mallorca	9.396	38.4	24.2	1.7	18.6
Ibiza	1.670	17.1	35.2	14.8	23.0
Menorca	1.021	9.1	50.3	5.5	29.4
Balearics	12.087	33.0	27.9	3.8	20.1

Table 2. Descriptive Statistics of Air Passenger Arrivals

Statistics	Palma	Ibiza	Mahon	Balearics
Mean	27,297	5,746	3,640	36,683
Median	24,588	2,898	1,593	30,807
Maximum	76,272	23,816	16,437	10,6250
Minimum	3,003	508	283	3794
Std. Dev.	15,976	5,525	3,593	23,980
Skewness	0.86	1.23	1.32	0.88
Kurtosis	3.17	3.61	3.94	2.87
J-B	273.46	590.10	721.53	282.27
Prob.	0.00	0.00	0.00	0.00

Table 3. Descriptive Statistics of Weekly Difference of Air Passenger Arrivals

Statistics	Palma	Ibiza	Mahon	Balearics
Mean	9.37	1.58	0.69	11.63
Median	253.0	32.5	17.0	380.5
Maximum	19195	7673	8153	27435
Minimum	-26446	-6303	-8118	-32234
Std. Dev.	3671	1153	888	5115
Skewness	-0.52	0.15	0.276	-0.41
Kurtosis	8.24	8.99	25.05	7.55
J-B	2597.0	3276.3	44275.1	1945.7
Prob.	0.00	0.00	0.00	0.00

Table 4. Unit Root Tests for the Balearic Islands

Variables	$MADF^{GLS}$	MPP^{GLS}	Lags	Z
y_t	-2.984**	-17.118*	22	(1,t)
y_t	-2.138**	-8.933**	22	(1)
$\Delta_7\ y_t$	-5.853***	-48.393***	24	(1,t)
$\Delta_7\ y_t$	-5.118***	-36.038***	19	(1)

Notes:
Y_t denotes passenger arrivals to the Balearic Islands.
(1,t) and (1) denote the presence of an intercept and trend, and intercept, respectively.
(***), (**) and (*) denote the null hypothesis of a unit root is rejected at the 1%, 5% and 10% significance levels respectively.

Critical Values				
%	$MADF^{GLS}$		MPP^{GLS}	
	Z=(1,t)	Z=(1)	Z=(1,t)	Z=(1)
1	-3.480	-2.566	-23.80	-13.80
5	-2.890	-1.941	-17.30	-8.10
10	-2.570	-1.617	-14.20	-5.70

Table 5. Unit Root Tests for Ibiza

Variables	$MADF^{GLS}$	MPP^{GLS}	Lags	Z
y_t	-3.345**	-21.542**	22	(1,t)
y_t	-2.608***	-13.083**	22	(1)
$\Delta_7\ y_t$	-4.882***	-31.751***	22	(1,t)
$\Delta_7\ y_t$	-3.514***	-16.940***	20	(1)

Notes:
Y_t denotes passenger arrivals to Ibiza.
(1,t) and (1) denote the presence of an intercept and trend, and intercept, respectively.
(***), (**) and (*) denote the null hypothesis of a unit root is rejected at the 1%, 5% and 10% significance levels respectively.
Critical values are given in the notes of table 4.

Table 6. Unit Root Tests for Menorca

Variables	$MADF^{GLS}$	MPP^{GLS}	Lags	Z
y_t	-2.988**	-15.232*	25	(1,t)
y_t	-2.396**	-10.076**	25	(1)
$\Delta_7\, y_t$	-5.723***	-36.926***	25	(1,t)
$\Delta_7\, y_t$	-4.865***	-25.219***	25	(1)

Notes:
Y_t denotes passenger arrivals to Menorca.
(1,t) and (1) denote the presence of an intercept and trend, and intercept, respectively.
(***), (**) and (*) denote the null hypothesis of a unit root is rejected at the 1%, 5% and 10% significance levels respectively.
Critical values are given in the notes of table 4.

Table 7. Unit Root Tests for Mallorca

Variables	$MADF^{GLS}$	MPP^{GLS}	Lags	Z
y_t	-2.827*	-14.215*	20	(1,t)
y_t	-1.938*	-7.135*	20	(1)
$\Delta_7\, y_t$	-6.252***	-53.907***	20	(1,t)
$\Delta_7\, y_t$	-5.830***	-44.648***	20	(1)

Notes:
Y_t denotes passenger arrivals to Mallorca.
(1,t) and (1) denote the presence of an intercept and trend, and intercept, respectively.
(***), (**) and (*) denote the null hypothesis of a unit root is rejected at the 1%, 5% and 10% significance levels respectively.
Critical values are given in the notes of table 4.

Table 8. Conditional Mean and Conditional Volatility Models for the Balearic Islands

Model 1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	453.315 (108.568)	457.885 (114.765)	648.341 (77.049)
ϕ_1	0.033 (0.004)	0.034 (0.004)	0.029 (0.005)
ϕ_2	0.965 (0.004)	0.965 (0.004)	0.964 (0.005)
ω	1893301 (160514)	1884235 (162717)	2.777 (0.362)
GARCH/GJR α	0.607 (0.032)	0.615 (0.038)	--
GJR γ	--	-0.015* (0.056)	--
GARCH/GJR β	0.423 (0.015)	0.424 (0.016)	--
EGARCH α	--	--	0.913 (0.065)
EGARCH γ	--	--	0.002* (0.036)
EGARCH β	--	--	0.789 (0.023)
Diagnostics			
Second moment	1.030	1.032	--
Log-moment	-0.236	-0.235	--
Log likelihood	-21123.80	-21123.77	-21114.61

Notes:
Y_t is the number of passenger arrivals to the Balearic Islands.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 9. Conditional Mean and Conditional Volatility Models for Ibiza

$$\text{Model 1: } y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	-6.459* (8.507)	3.450* (7.887)	10.073* (7.797)
ϕ_1	0.069 (0.009)	0.069 (0.009)	0.065 (0.009)
ϕ_2	0.943 (0.009)	0.943 (0.009)	0.938 (0.010)
ω	5609.17 (1687.87)	4881.85 (1553.8)	0.132* (0.101)
GARCH/GJR α	0.584 (0.096)	0.687 (0.145)	--
GJR γ	--	-0.215* (0.118)	--
GARCH/GJR β	0.621 (0.031)	0.628 (0.029)	--
EGARCH α	--	--	0.741 (0.072)
EGARCH γ	--	--	0.064* (0.036)
EGARCH β	--	--	0.950 (0.009)
Diagnostics			
Second moment	1.205	1.207	--
Log-moment	-0.040	-0.036	--
Log likelihood	-17509.12	-17500.62	-17485.24

Notes:
Y_t is the number of passenger arrivals to Ibiza.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 10. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model 1: } y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	49.363 (12.696)	38.530 (8.982)	9.816* (8.959)
ϕ_1	0.019 (0.007)	0.044 (0.015)	0.054 (0.016)
ϕ_2	0.935 (0.014)	0.933 (0.018)	0.960 (0.010)
ω	3901.36 (1982.45)	3439.42* (1851.82)	0.217* (0.123)
GARCH/GJR α	0.565 (0.100)	0.623 (0.093)	--
GJR γ	--	-0.201* (0.128)	--
GARCH/GJR β	0.658 (0.047)	0.682 (0.048)	--
EGARCH α	--	--	0.668 (0.049)
EGARCH γ	--	--	0.032* (0.043)
EGARCH β	--	--	0.948 (0.010)
Diagnostics			
Second moment	1.223	1.204	--
Log-moment	-0.041	-0.036	--
Log likelihood	-16971.17	-16963.09	-16948.19

Notes:
Y_t is the number of passenger arrivals to Menorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level

Table 11. Conditional Mean and Conditional Volatility Models for Mallorca

$$\text{Model 1: } y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	347.610 (93.669)	351.747 (102.472)	395.08 (73.38)
ϕ_1	0.026 (0.004)	0.026 (0.004)	0.024 (0.005)
ϕ_2	0.970 (0.004)	0.970 (0.004)	0.970 (0.005)
ω	847635.2 (83926.5)	822707.9 (87087.9)	1.406 (0.428)
GARCH/GJR α	0.426 (0.027)	0.446 (0.031)	--
GJR γ	--	-0.037* (0.040)	--
GARCH/GJR β	0.579 (0.013)	0.582 (0.014)	--
EGARCH α	--	--	0.632 (0.063)
EGARCH γ	--	--	0.005* (0.029)
EGARCH β	--	--	0.882 (0.029)
Diagnostics			
Second moment	1.005	1.009	--
Log-moment	-0.151	-0.146	--
Log likelihood	-20562.94	-20562.63	-20564.95

Notes:
Y_t is the number of passenger arrivals to Mallorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 12. Conditional Mean and Conditional Volatility Models for the Balearic Islands

Model 2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	76.315* (52.264)	99.97* (58.26)	120.016 (55.471)
ϕ_1	0.719 (0.016)	0.720 (0.016)	0.718 (0.020)
ω	865607.1 (52528.4)	847195.9 (58519.65)	1.355 (0.545)
GARCH/GJR α	0.325 (0.016)	0.357 (0.020)	--
GJR γ	--	-0.063 (0.032)	--
GARCH/GJR β	0.663 (0.011)	0.667 (0.013)	--
EGARCH α	--	--	0.513 (0.068)
EGARCH γ	--	--	0.032* (0.048)
EGARCH β	--	--	0.893 (0.035)
Diagnostics			
Second moment	0.989	0.992	--
Log-moment	-0.131	-0.127	--
Log likelihood	-20667.22	-20666.22	-20665.16

Notes:
Y_t is the number of passenger arrivals to the Balearic Islands.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 13. Conditional Mean and Conditional Volatility Models for Ibiza

$$\text{Model 2: } \Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	2.277* (11.490)	16.117* (8.402)	17.333* (8.422)
ϕ_1	0.588 (0.025)	0.592 (0.027)	0.609 (0.025)
ω	3980.83 (1323.60)	3088.4 (1149.9)	-0.026 (0.063)
GARCH/GJR α	0.442 (0.089)	0.540 (0.153)	--
GJR γ	--	-0.249* (0.158)	--
GARCH/GJR β	0.706 (0.029)	0.724 (0.026)	--
EGARCH α	--	--	0.419 (0.025)
EGARCH γ	--	--	0.067* (0.034)
EGARCH β	--	--	0.979 (0.005)
Diagnostics			
Second moment	1.148	1.140	--
Log-moment	-0.028	-0.023	--
Log likelihood	-17256.36	-17240.90	-17232.11

Notes:
Y_t is the number of passenger arrivals to Ibiza.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 14. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model 2: } \Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	6.668* (7.511)	10.544 (6.867)	12.98 (6.317)
ϕ_1	0.567 (0.045)	0.569 (0.043)	0.581 (0.050)
ω	3609.47 (1500.46)	3355.35 (1465.31)	0.135* (0.110)
GARCH/GJR α	0.632 (0.066)	0.719 (0.093)	--
GJR γ	--	-0.181* (0.171)	--
GARCH/GJR β	0.655 (0.024)	0.658 (0.025)	--
EGARCH α	--	--	0.590 (0.045)
EGARCH γ	--	--	0.061* (0.049)
EGARCH β	--	--	0.959 (0.009)
Diagnostics			
Second moment	1.286	1.287	--
Log-moment	-0.040	-0.038	--
Log likelihood	-16807.55	-16804.78	-16781.85

Notes:
Y_t is the number of passenger arrivals to Menorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 15. Conditional Mean and Conditional Volatility Models for Mallorca

$$\text{Model 2: } \Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	54.11* (38.50)	54.073* (49.203)	45.844 (58.130)
ϕ_1	0.628 (0.014)	0.628 (0.015)	0.616 (0.028)
ω	588188.8 (37279.4)	588119.1 (41991.4)	1.083 (0.468)
GARCH/GJR α	0.295 (0.020)	0.294 (0.023)	--
GJR γ	--	0.000* (0.029)	--
GARCH/GJR β	0.688 (0.015)	0.687 (0.016)	--
EGARCH α	--	--	0.458 (0.044)
EGARCH γ	--	--	0.008* (0.047)
EGARCH β	--	--	0.911 (0.031)
Diagnostics			
Second moment	0.982	0.982	--
Log-moment	-0.129	-0.129	--
Log likelihood	-20212.37	-20212.37	-20205.71

Notes:
Y_t is the number of passenger arrivals to Mallorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 16. Conditional Mean and Conditional Volatility Models for the Balearic Islands

$$\text{Model 3: } y_t = \phi_0 + \phi_1 \delta_{\text{H}} y_{t-1} + \phi_2 \delta_{\text{H}} y_{t-7} + \phi_3 \delta_{\text{L}} y_{t-1} + \phi_4 \delta_{\text{L}} y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	338.097 (163.42)	341.78* (183.48)	419.08 (201.67)
ϕ_1	0.039 (0.005)	0.038 (0.005)	0.038 (0.006)
ϕ_2	0.961 (0.005)	0.961 (0.005)	0.958 (0.006)
ϕ_3	0.022* (0.014)	0.022* (0.014)	0.014* (0.009)
ϕ_4	0.987 (0.012)	0.987 (0.013)	0.999 (0.009)
ω	1840217 (157984)	1830796 (159205)	2.798 (0.342)
GARCH/GJR α	0.614 (0.033)	0.623 (0.040)	--
GJR γ	--	-0.016* (0.061)	--
GARCH/GJR β	0.424 (0.016)	0.425 (0.017)	--
EGARCH α	--	--	0.931 (0.063)
EGARCH γ	--	--	0.001* (0.035)
EGARCH β	--	--	0.787 (0.022)
Diagnostics			
Second moment	1.038	1.039	--
Log-moment	-0.232	-0.231	--
Log likelihood	-21121.42	-21121.38	-21107.24

Notes:
Y_t is the number of passenger arrivals to the Balearic Islands.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 17. Conditional Mean and Conditional Volatility Models for Ibiza

$$\text{Model 3: } y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	30.12* (48.54)	25.986* (52.119)	-7.852* (53.585)
ϕ_1	0.049 (0.011)	0.047 (0.011)	0.053 (0.011)
ϕ_2	0.967 (0.011)	0.967 (0.010)	0.949 (0.012)
ϕ_3	0.176 (0.023)	0.178 (0.024)	0.177 (0.023)
ϕ_4	0.808 (0.024)	0.814 (0.026)	0.834 (0.028)
ω	5507.47 (1696.98)	4820.05 (1594.94)	0.101* (0.092)
GARCH/GJR α	0.612 (0.097)	0.723 (0.145)	--
GJR γ	--	-0.219* (0.115)	--
GARCH/GJR β	0.609 (0.028)	0.614 (0.030)	--
EGARCH α	--	--	0.751 (0.074)
EGARCH γ	--	--	0.058* (0.037)
EGARCH β	--	--	0.951 (0.008)
Diagnostics			
Second moment	1.221	1.227	--
Log-moment	-0.039	-0.035	--
Log likelihood	-17483.46	-17475.84	-17470.45

Notes:
Y_t is the number of passenger arrivals Ibiza.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 18. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model 3: } y_t = \phi_0 + \phi_1\delta_{\mathrm{H}}\, y_{t-1} + \phi_2\delta_{\mathrm{H}}\, y_{t-7} + \phi_3\delta_{\mathrm{L}}\, y_{t-1} + \phi_4\delta_{\mathrm{L}}\, y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	321.24 (50.82)	313.82 (48.757)	263.17 (39.26)
ϕ_1	0.010* (0.008)	0.010* (0.008)	0.019 (0.009)
ϕ_2	0.974 (0.007)	0.974 (0.008)	0.971 (0.009)
ϕ_3	0.066* (0.037)	0.065* (0.036)	0.117 (0.031)
ϕ_4	0.606 (0.031)	0.607 (0.031)	0.607 (0.029)
ω	2759.93 (1004.44)	2717.0 (987.9)	0.085* (0.089)
GARCH/GJR α	0.683 (0.083)	0.703 (0.101)	--
GJR γ	--	-0.039* (0.130)	--
GARCH/GJR β	0.608 (0.021)	0.608 (0.021)	--
EGARCH α	--	--	0.731 (0.053)
EGARCH γ	--	--	0.006* (0.043)
EGARCH β	--	--	0.953 (0.007)
Diagnostics			
Second moment	1.290	1.292	--
Log-moment	-0.034	-0.033	--
Log likelihood	-16855.85	-16855.65	-16836.10

Notes:
Y_t is the number of passenger arrivals to Menorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 19. Conditional Mean and Conditional Volatility Models for Mallorca

$$\text{Model 3: } y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	-63.040* (139.46)	-64.522* (165.45)	119.71* (198.43)
ϕ_1	0.033 (0.004)	0.032 (0.005)	0.030 (0.006)
ϕ_2	0.971 (0.005)	0.971 (0.005)	0.970 (0.006)
ϕ_3	0.034 (0.012)	0.034 (0.012)	0.026 (0.010)
ϕ_4	0.999 (0.011)	1.000 (0.011)	0.999 (0.011)
ω	768923.6 (80740.1)	738865.1 (80616.6)	1.284 (0.415)
GARCH/GJR α	0.428 (0.026)	0.455 (0.033)	--
GJR γ	--	-0.050* (0.042)	--
GARCH/GJR β	0.587 (0.014)	0.590 (0.014)	--
EGARCH α	--	--	0.641 (0.067)
EGARCH γ	--	--	0.012* (0.030)
EGARCH β	--	--	0.890 (0.028)
Diagnostics			
Second moment	1.015	1.020	--
Log-moment	-0.139	-0.134	--
Log likelihood	-20558.33	-20557.74	-20560.25

Notes:
Y_t is the number of passenger arrivals to Mallorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 20. Conditional Mean and Conditional Volatility Models for the Balearic Islands

$$\text{Model 4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\mathrm{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	87.68* (52.59)	123.036 (57.553)	185.51 (53.18)
ϕ_1	0.784 (0.017)	0.791 (0.016)	0.795 (0.025)
ϕ_2	0.560 (0.046)	0.556 (0.045)	0.567 (0.031)
ω	852491.3 (52506.5)	818845.7 (58495.9)	1.252 (0.538)
GARCH/GJR α	0.300 (0.016)	0.348 (0.020)	--
GJR γ	--	-0.095 (0.030)	--
GARCH/GJR β	0.679 (0.012)	0.684 (0.014)	--
EGARCH α	--	--	0.486 (0.066)
EGARCH γ	--	--	0.050* (0.049)
EGARCH β	--	--	0.901 (0.035)
Diagnostics			
Second moment	0.979	0.984	--
Log-moment	-0.128	-0.123	--
Log likelihood	-20651.73	-20649.41	-20651.31

Notes:
Y_t is the number of passenger arrivals to the Balearic Islands.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 21. Conditional Mean and Conditional Volatility Models for Ibiza

$$\text{Model 4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\mathrm{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	0.769* (10.867)	18.15 (7.778)	30.214 (7.310)
ϕ_1	0.688 (0.032)	0.721 (0.034)	0.737 (0.034)
ϕ_2	0.418 (0.035)	0.397 (0.035)	0.381 (0.034)
ω	3794.4 (1240.22)	2590.82 (1010.17)	-0.030* (0.069)
GARCH/GJR α	0.430 (0.080)	0.542 (0.132)	--
GJR γ	--	-0.317 (0.159)	--
GARCH/GJR β	0.710 (0.026)	0.743 (0.018)	--
EGARCH α	--	--	0.417 (0.028)
EGARCH γ	--	--	0.109 (0.043)
EGARCH β	--	--	0.980 (0.005)
Diagnostics			
Second moment	1.141	1.126	--
Log-moment	-0.028	-0.020	--
Log likelihood	-17235.92	-17212.12	-17200.87

Notes:
Y_t is the number of passenger arrivals to Ibiza.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 22. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model 4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\text{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\text{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	5.769*	12.014	18.504
	(6.569)	(5.873)	(5.084)
ϕ_1	0.724	0.740	0.755
	(0.050)	(0.052)	(0.054)
ϕ_2	0.382	0.373	0.391
	(0.034)	(0.034)	(0.036)
ω	3584.42	3173.85	0.160*
	(1396.91)	(1302.53)	(0.118)
GARCH/GJR α	0.651	0.825	--
	(0.063)	(0.097)	
GJR γ	--	-0.350	--
		(0.149)	
GARCH/GJR β	0.639	0.644	--
	(0.023)	(0.025)	
EGARCH α	--	--	0.619
			(0.045)
EGARCH γ	--	--	0.103
			(0.042)
EGARCH β	--	--	0.955
			(0.010)
Diagnostics			
Second moment	1.289	1.294	--
Log-moment	-0.042	-0.038	--
Log likelihood	-16783.43	-16776.54	-16755.24

Notes:
Y_t is the number of passenger arrivals to Menorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 23. Conditional Mean and Conditional Volatility Models for Mallorca

$$\text{Model 4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\mathrm{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	62.871* (39.180)	60.142* (49.873)	50.562* (61.832)
ϕ_1	0.665 (0.015)	0.666 (0.016)	0.636 (0.040)
ϕ_2	0.555 (0.043)	0.556 (0.043)	0.576 (0.035)
ω	587291.0 (37214)	590619 (42164)	1.084 (0.478)
GARCH/GJR α	0.278 (0.020)	0.272 (0.022)	--
GJR γ	--	0.010* (0.028)	--
GARCH/GJR β	0.698 (0.015)	0.698 (0.017)	--
EGARCH α	--	--	0.449 (0.043)
EGARCH γ	--	--	0.008* (0.048)
EGARCH β	--	--	0.911 (0.031)
Diagnostics			
Second moment	0.976	0.975	--
Log-moment	-0.128	-0.128	--
Log likelihood	-20209.05	-20209.03	-20204.17

Notes:
Y_t is the number of passenger arrivals to Mallorca.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant at the 5% level.

Table 24. Likelihood Ratio Tests of Constancy of Coefficients in High and Low Seasons

H_0: Model 1 **H_1: Model 3**	**GARCH**	**GJR**	**EGARCH**
Balearics	4.76*	4.78*	14.74
Ibiza	51.32	49.56	29.58
Menorca	230.64	214.88	224.18
Mallorca	9.22	9.78	9.40

H_0: Model 2 **H_1: Model 4**	**GARCH**	**GJR**	**EGARCH**
Balearics	30.98	33.62	27.70
Ibiza	40.88	57.56	62.49
Menorca	48.24	56.48	53.22
Mallorca	6.64	6.68	3.08*

Note:
(*) indicates that the likelihood ratio test statistic is not significant at the 5% level, where $X^2(2) = 5.991$; otherwise, all test statistics are significant at the 5% level.