Risk Management for International Tourist Arrivals:

An Application to Spain

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Research Report for the PhD program

“Globalització Econòmica i Benestar Social”

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Universitat de les Illes Balears

November 2007

I wish to thank so very much Dr. Michael McAleer
for his outstanding teaching.

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Chapter 1. INTRODUCTION

1.1 Tourism as an important service industry

According to the United Nations World Tourism Organization, in 2006 international tourist arrivals increased by 5% worldwide (UNWTO, 2007). It is widely acknowledged that tourism is important economically, socially and culturally. Therefore, an analysis of international tourism demand across and within countries is crucial for understanding its global and regional impact.

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).

An explanation for the lack of detailed economic analysis in tourism, which has been suggested by Sinclair and Stabler (1997) and Tisdell (2000), among others, stems from the low priority given to services in economic studies historically. This explains the lack of data and the national and regional accounting classifications that would be able to contribute to the economic analysis of tourism. Smith (1998) also notes that the heterogeneous and unconventional nature of tourism has typically led to the unavailability of appropriate data.

However, certain types of time series data have recently become available for key sectors of the economy, including tourism. This data development has provided opportunities for applying analytical tools that were originally designed for other disciplines, such as finance. For purposes of a more detailed empirical analysis, there are now sources that provide data at the weekly and monthly frequencies. However, there are still few sources that provide data at the high (that is, daily or hourly) or ultra high (that is, observations by the minute or second) frequencies, as are typically available in finance.

It is clear that international tourist arrivals are important globally. In the case of Spain, in 2006 the growth rate was 4.7%, but this rate varies considerably across the five main tourism regions in Spain, from 1.5% in the "Comunidad Valenciana" (or Valencia) to 6.9% in Catalonia (IET, 2006b). Spain is especially known for its standardized sun and sand tourism. Despite doubts about the long run sustainability of this tourism segment in some mature tourist destinations (Buhalis (2001), Poon (1993)), this form of tourism remains one of the pillars of the Spanish economy. In fact, the tourism industry represents approximately 9.8% of the labour force (Exceltur, 2007).

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 changes, and their associated time-varying volatilities, can make a significant contribution to tourism risk management and marketing.

1.2 Contribution of this research report

Tourism research has recognized the vulnerability of international tourism demand to natural disasters, terrorism, financial crisis, political instability, etc. These studies have mainly focused on post-event analysis (Bonn and Rundle-Thiele 2007; Eugenio-Martin, Sinclair, and Yeoman 2005; Huang and Min 2002; Law 2001; Song and Li 2008), and although this analysis is important, pre-event risk assessment seems be to be crucial for an effective tourism management, at the macro level and at the micro level. One of the primary purposes of this research report is to extend the ideas of uncertainty to the issue of spatial aggregation across micro entities, to more aggregated macro entities, 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 firstly across the five main Spanish tourist regions and secondly 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 study introduces three other types of asymmetric behaviour, namely low season financial risk, overcrowding through overbooking and congestion, and tourism saturation.

1.3 Outline of the report

The overall structure of this research report is at the following. It consists of an introduction (Chapter 1) that provides an overview of the research report, research issues and justification. In Chapter 2 the recent development of literature related to risk management and to financial econometrics applied to tourism is reviewed. The Chapter also examines the developments and statistical properties of univariate models of conditional volatility. Chapter 3 provides an overview of the tourism industry in Spain and in the five main tourist regions. It then follows with an analysis of the Balearic Islands from an economic perspective. The estimated models and empirical results for the monthly international tourist arrivals to Spain and the five main tourist regions are discussed in Chapter 4, and the same for daily passenger arrivals to the Balearic Islands in Chapter 5. Finally some concluding remarks are given in Chapter 6. This chapter also provides directions for further research, and justifies the validity and contribution of this study.

This chapter has laid the foundations for this research report. Firstly it has provided evidence of the importance of the tourism industry 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 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.

Chapter 2. CONDITIONAL MEAN AND CONDITIONAL VOLATILITY MODELS: APPLICATIONS TO TOURISM DEMAND

2.1 Introduction

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 Kim and Wong (2006) and 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. Furthermore, it has been proved that the assumption of (conditionally) homoskedastic residuals is inappropriate (see, for example, Li, Ling and McAleer (2002), and McAleer (2005)).

International tourism demand is important for many countries worldwide. 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.

2.2 The importance of modelling risk for international tourism demand

"History has consistently demonstrated a propensity to move beyond the expected with unexpected shocks that disrupt the smooth and ordered unfolding of human affairs"

(Prideaux, Laws and Faulkner, 2003)

Modelling and forecasting tourism demand has been a highly researched topic within the tourism economics literature. To illustrate this extensive research, it is enough to see the number of articles which review papers on modelling and forecasting tourism demand published in the academic literature. For example see Crouch (1994, 1995), Witt and Witt (1995) or Lim (1997a, 1997b, 1999). More recently, Li, Song and Witt (2005) revised a total of 84 studies between 1990 and 2004 and found that a total of 420 studies were published in the period 1960-2002 covering the topic of tourism demand modelling and forecasting. Furthermore this topic continues to be relevant as new ways of modelling are developed. Song and Li (2008) review a total of 121 papers published in the period 2000-2007. In this paper, Song and Li state that although risk forecasting is of great importance for tourism practitioners, such as tourism business executives and government offices, it has received little attention in the academic literature.

Faulkner and Russell (2000) suggest that the mechanistic Newtonian-Cartesian paradigm is not sufficient to understand reality and in particular, for understanding tourism systems. They suggest science should move into a more complex framework. Under the statement "the certainty of the unexpected", the chaos and complexity model seems to explain and understand better the reality, because tourism systems are unstable, unpredictable, multidimensional and in a state of constant change (Faulkner and Russell, 2000; Faulkner and Russell, 2002; Russell and Faulkner, 1999). In fact, the chaos theory has been applied in tourism research and in particular at the destination level, for instance, Prideaux, Laws and Faulkner (2003) in Indonesia or Russel and Faulkner (1999) in Australia. Furthermore, Prideaux *et al* (2003) recognize the "inability of current forecasting theory to cope with the unexpected" and therefore suggest the need of risk analysis to minimize the negative effects on tourism as a consequence of an unexpected event.

According to Floyd, Gibson, Pennington-Gray and Thapa (2003), the literature has identified five major risk factors significant to tourism:

- Political instability;
- Health;
- Crime;
- Terrorism; and
- Natural disasters.

On the other hand, Santana (2003) classifies these factors between socio-economic and nature/technological and between normal and severe he then identifies eight different groups:

- Psychopath Behaviour, such as terrorism and crime;
- Conflicts, such as wars;
- Infrastructure, for example over-development and saturation;
- Health, such as contamination and epidemics;
- Natural Disasters, like Floods, Tsunamis, Earthquakes;
- System Failures, such as transport accidents;
- Market, e.g. competition, strikes or image; and
- Communication, such as false advertising or ambush interviews.

Risk in finance, is measured by the volatility which is defined as the squared deviation from the mean. As, by definition, risk is ex ante (Skalpe, 2003), the issue of interest is to be able to forecast the expected value of this volatility (or the conditional volatility).

It is worth mentioning that the scarce literature existing on how unexpected events affect the tourism industry, are mainly, if not only, focused on negative shocks, and the negative consequences on tourism arrivals. It must be recognized that there are more possible outcomes associated with the uncertainty. Firstly, shocks can also be positive, and affect positively the tourism industry, for example a destination chosen to host the Olyimpic games or America's Cup. There are many studies on economic impact and expected revenues from an event of this type (Daniels and Norman, 2003; Daniels, Norman and Henry, 2004; Gelan, 2003; Hodur, Bangsund, Leistritz and Kaatz, 2006), but this type of shock is treated in a considerably different way. Impacts and forecasts are studied on the basis of certainty, i.e. it is not an unpredictable shock (Chan, Hui and Yuen, 1999). Secondly, positive shocks may have a negative effect on tourism, for instance, it has been suggested that if a destination is working at full capacity, and cannot cater for any more tourists, a positive shock should not be desirable for optimal management purposes. Moreover, an unsatisfactory experience will have a negative effect on a possible repeat visit in the future (Alegre and Cladera, 2006). Finally, a third scenario would be a negative shock delivering a positive effect on tourism demand. For instance, it could happen that a negative shock may affect a certain type of tourists but simultaneously or consequently, the destination can become appealing to a new and more desirable tourist.

Prideaux *et al* (2003) classify the factors that can suddenly and unpredictably disrupt tourism demand for a destination. This classification is the following:

1. *Inhibiting factors*: These factors affect tourists in their own country of origin. Such as an economic recession, political instability or unfavourable exchange rates.
2. *Diverting factors*: These are related to other destinations which may offer better facilities, better prices or better connections, and consequently persuade tourists from coming to our destination and travel to a competitive destination. For example Kozac, examined the competitive situation between Mallorca, in Spain and Mugla, in Turkey (Kozak, 2001a; Kozak, 2001b; Kozak, 2002). However, as Hoti *et al* (2007) found, some destinations may be complementary and therefore a negative shock in one destination will have the same sign effect on another destination, such as the case of Cyprus

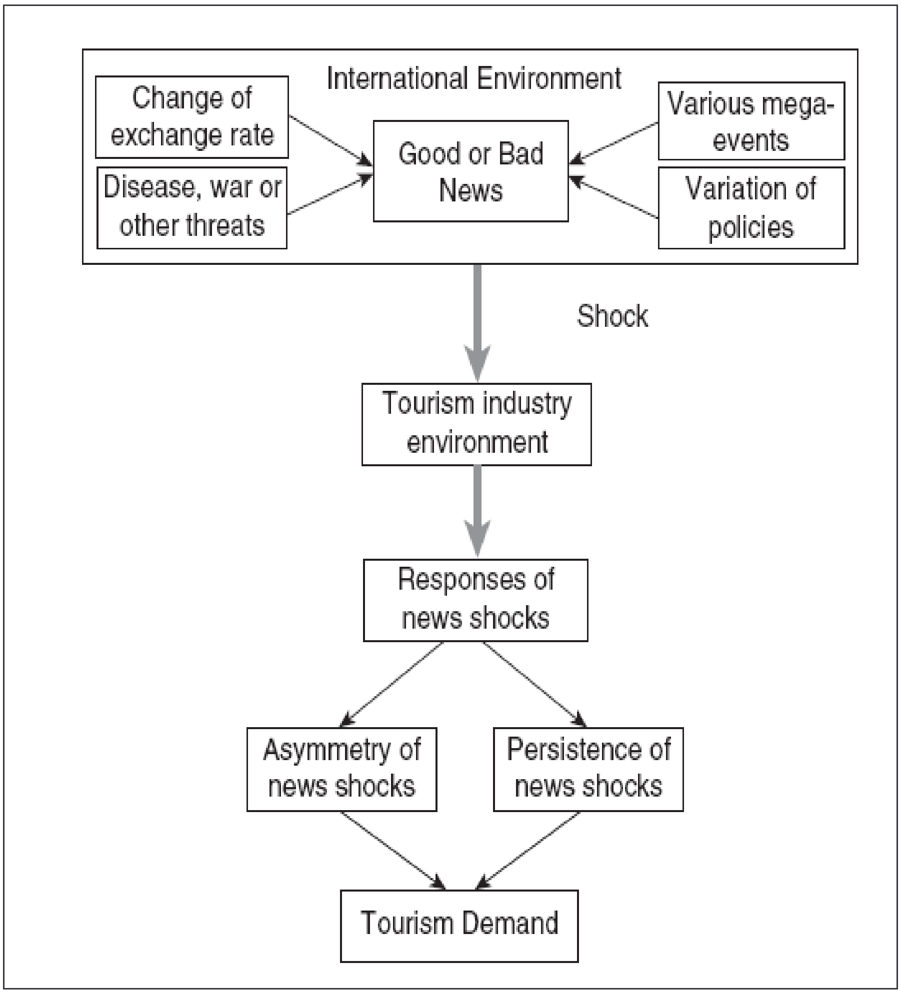
and Malta. In fact these factors could also be considered as spillover effects or externalities.

3. *Repelling factors*: Factors which occur at the tourist destination, such as natural disasters (eg Tsunami) or political unrest (eg. Coup d'état).

As emphasized in the introduction, the ultimate purpose of modelling risk is to assist in managing decision making. In the particular case of daily arrivals, the analysis of daily data permits studying the short run effect of shocks. Nowadays, this analysis is crucial for management purposes. In tourism, where the nature of the service product is perishable, having information on the expected number of tourist arrivals and their variance is indispensable for an efficient management policy. Furthermore, according to Poon, (1993) tourists are changing the way in which they plan their holiday; they are booking and paying closer to the departure date, this behaviour is becoming more unpredictable and therefore more volatile (Alegre and Cladera, 2006). The appearance and rapid growth of low cost airlines is also promoting this new trend in consumers' behaviour (Williams, 2001), not only for the flexibility it provides an increasingly independent traveller (Vanhove, 2001), but also, the low cost market is characterized by its spectacular growth and for its high volatility (Francis, Humphreys and Ison, 2004). While in 1998, Sönmez suggested that the tourism businesses were affected about three months after a terrorist attack as tourists had already booked and paid for the holidays (Sönmez, 1998), Floyd *et al* (2003), noted that after the terrorist attack of September 11, 2001 the impact on tourism was immediate. Having all this in mind, modelling the short run effect of shocks seems to be crucial for the tourism industry, from a macro perspective (transport, taxes) and from a micro perspective (business management).

Kim and Wong (2006) develop the following diagram, which provides a good synthesis on how news impacts on volatility of tourism demand. Different events or situations will deliver certain types of news (good or bad) also known as shocks (positive or negative), these will then have an effect on consumers decisions whether or not to travel to a certain destination. This deviation from the expected value or mean, squared, is defined as volatility or risk. Additionally the shock effect might have short run persistence and/or long run persistence, and possibly will have a different effect depending whether there are positive or negative shocks. Therefore, news is likely to affect tourism demand.

Figure 1. News Impacts on Volatility of Tourism Demand



(Source: Kim & Wong, 2006)

As it has been proved that the conditional variance cannot be considered constant or homoskedastic (Li, Ling and McAleer, 2002; McAleer, 2005), it is necessary to apply heteroskedastic models. The following section will review the econometric theory background for estimating the conditional mean and the conditional variance using the financial GARCH(1,1), GJR(1,1) and EGARCH(1,1) univariate models.

2.3The AR(1)-GARCH(1,1) Model

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 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) 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.

2.4 The GJR(1,1) Model

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:

$$\alpha + \beta + \frac{1}{2}\gamma < 1, \qquad (5)$$

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

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

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

2.5 The EGARCH(1,1) Model

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

$$\log h_t = \omega + \alpha \mid \eta_{t-1} \mid + \gamma \eta_{t-1} + \beta \log h_{t-1}, \quad \mid \beta \mid < 1 \qquad (7)$$

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 $\mid \beta \mid < 1$ 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).

Interpretation of Asymmetries in EGARCH(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 1 to 4), there are four possible scenarios of asymmetry in the EGARCH model, according to the restrictions on α and γ, as follows:

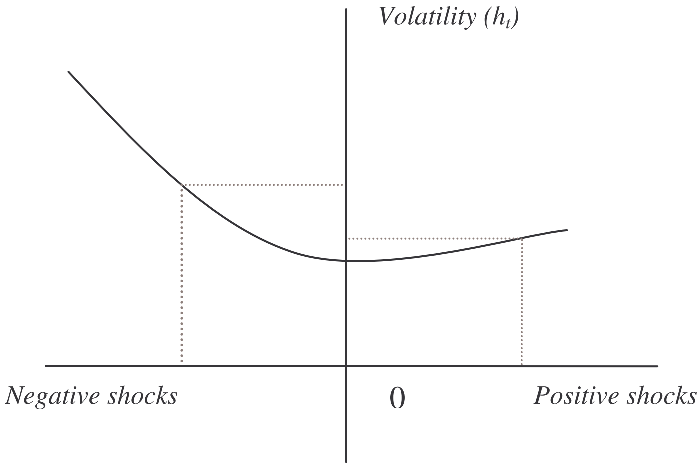
(i) **Type 1 Asymmetry**: Low Season Financial Risk, in which negative shocks increase volatility and positive shocks of a similar magnitude increase volatility by a smaller amount. In this case, the slope of a negative shock is negative whereas the slope of a positive shock is positive. What distinguishes this case from the symmetric model, is that the slope of a negative shock is steeper than the slope of the positive shock and therefore :

$$\alpha > 0$$

and,

$$-\alpha < \gamma < 0$$

Figure 2. Type 1 Asymmetry: Low Season Financial Risk
($\alpha > 0$, $-\alpha < \gamma < 0$)



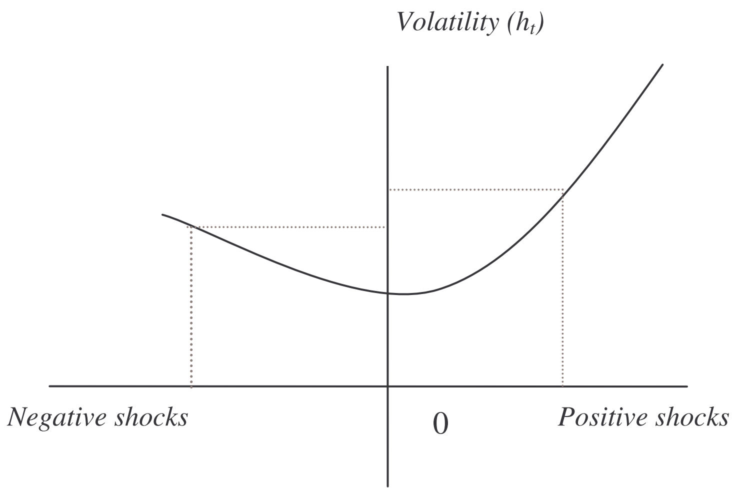
(ii) **Type 2 Asymmetry**: Overbooking Pressure on Carrying Capacity, in which negative shocks increase volatility and positive shocks of similar magnitude increase volatility by a larger amount. In other words, the slope of a negative shock on volatility is negative and smother than the positive slope of a positive shock on the volatility and then

$$\alpha > 0$$

and,

$$0 < \gamma < \alpha$$

Figure 3. Type 2 Asymmetry: Overbooking Pressure on Carrying Capacity
($\alpha > 0$, $0 < \gamma < \alpha$)



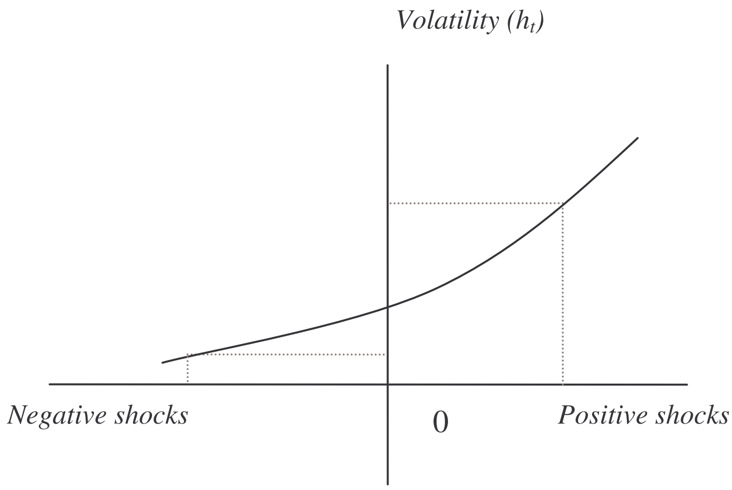
(iii) **Type 3 Asymmetr**y: Tourism Saturation in High Season, in which negative shocks decrease volatility and positive shocks of a similar magnitude increase volatility, consequently both slopes corresponding to negative and positive shock are positive,

$$\gamma > 0$$

and,

$$-\gamma < \alpha < \gamma$$

Figure 4. Type 3 Asymmetry: Tourism Saturation in High Season
($\gamma > 0$, $-\gamma < \alpha < \gamma$)



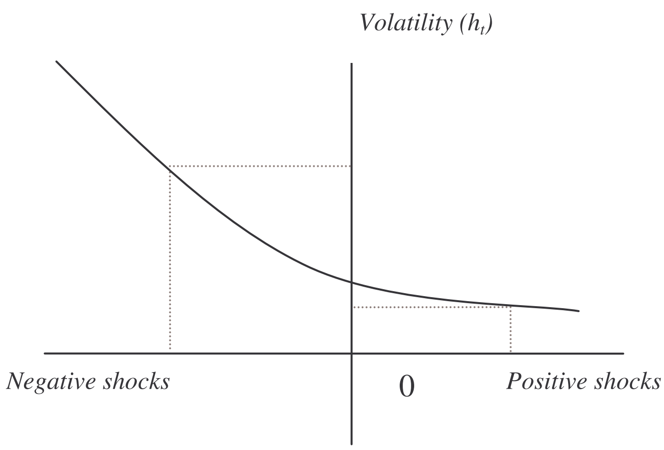
(iv) **Type 4 Asymmetry:** Leverage and Tourism Downturn, in which negative shocks increase volatility and positive shocks of a similar magnitude decrease volatility, because the slope of positive and negative shocks is negative,

$$\gamma < 0$$

and,

$$\gamma < \alpha < - \gamma$$

Figure 5. Type 4 Asymmetry: Leverage and Tourism Downturn
($\gamma < 0$, $\gamma < \alpha < - \gamma$)



2.6 Conclusion

This chapter has given the most recent theoretical results for the univariate GARCH; GJR and EGARCH models of conditional volatility developed by Engle (1982), with subsequent developments by Bollerslev (1986). It has also reviewed the necessary and sufficient conditions for the existence of the second moment and of the log moment, found in the literature. Additionally, this section has given an interpretation of the estimated coefficients of the conditional variance. Furthermore it has developed four possible scenarios of asymmetry in the EGARCH model, according to the restrictions on α and γ, and interpreting the results in accordance to the applicability to tourism.

Chapter 3. TOURISM IN SPAIN AND IN THE BALEARIC ISLANDS.

3.1 Introduction

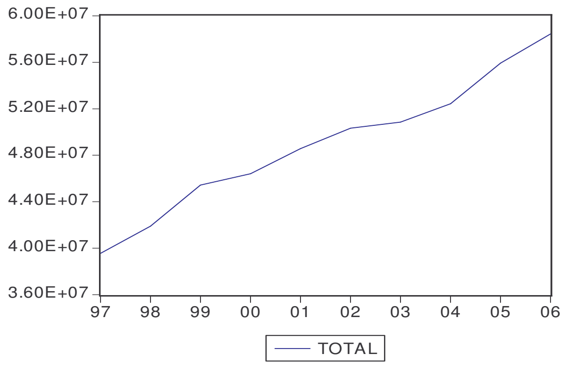
One fact that characterizes the evolution of many destinations around the world, including Spain, has been the decentralizing process of tourism policies towards a regional level (Ivars, 2004). Consequently this third chapter starts by studying the contribution of the tourism industry to the Spanish economy and provides the characteristics and economic impacts of tourism for the five major tourist regions in 2006. It then follows an analysis of the economic significance of tourism to the Balearic Islands and gives a snapshot of the composition of the tourist demand to the three different islands.

3.2 Tourism in Spain

In the last few decades, tourism has become one of the most prominent engines for the Spanish economy. Since the 1960’s, the number of international tourist arrivals has increased considerably. In fact, in 2006 Spain was the second largest country in the world in terms of the number of international tourist arrivals, after the leader France and ahead of USA, China, Italy and UK. Furthermore, it was also the second largest country in terms of international tourism receipts (UNWTO, 2007).

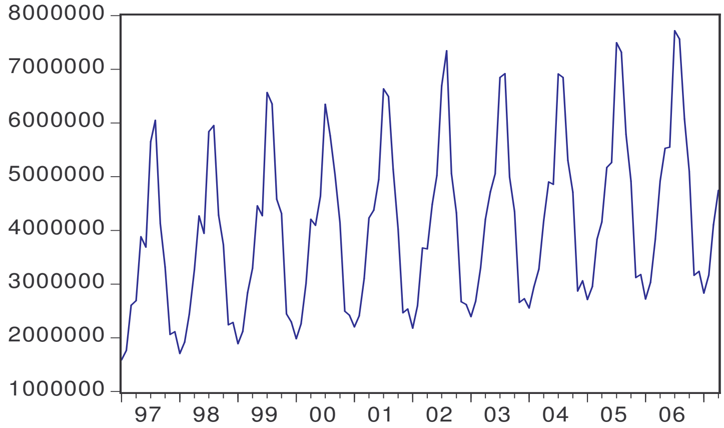
The main facts characterizing tourism in Spain are, firstly that tourism is still increasing, secondly the strong seasonality and third is that tourists and consequently tourism service providers seem to concentrate in five regions. A deeper analysis of these facts is provided below. In the last decade alone, the total number of international tourists who visited Spain rose from 39.5 million in 1997 to 58.5 million in 2006 (see Figure 6).

Figure 6. Yearly International Tourist Arrivals to Spain from 1997 to 2006



Regarding the distribution of arrivals along the years, as shown in Figure 7, the number of monthly international tourist arrivals to Spain has varied substantially across the summer and winter months, such that tourism seasonality is one of the main problems for tourism destination management. The number of tourist arrivals drops dramatically every November and does not recover until March. Therefore, the months between November and March are considered to be the low tourist season, and the high tourist season comprises the months between April and October. Also noticeable is the peak in the low tourist season during the Christmas holidays.

Figure 7. Monthly International Tourist Arrivals to Spain from January 1997 to April 2007



In 2006 Spain received a total of 58.5 million international tourists. The UK, Germany and France are the most important tourism generating markets, with these three countries accounting for more than one-half of total international tourist arrivals. The remainder of tourists originates mainly in the other countries in Europe. The long haul market is very small in comparison, with around 7% of international tourist arrivals coming from outside Europe (IET, 2006b). Finally, in regard to the geographical distribution of tourists in Spain, over 83.4% of total international tourist arrivals stay in one of the five major Spanish tourism regions of Andalusia, Balearics, Canaries, Catalonia and Valencia.

Figure 8 plots the evolution of the yearly international tourist arrivals to the five major tourism regions between 1997 and 2006. Outstanding is Catalonia, which in ten years has more than doubled the number of international tourist arrivals. The Balearic Islands and Canary Islands, which in 1997 were the most prominent Spanish tourism regions, now receive approximately the same number of yearly international tourist arrivals. Despite the slow growth rates, these two regions remain the second and third most important, respectively, in Spain. Andalusia and Valencia have maintained their fourth and fifth positions, respectively over these ten years, and both show a positive trend.

Figure 8. Yearly International Tourist Arrivals by Region

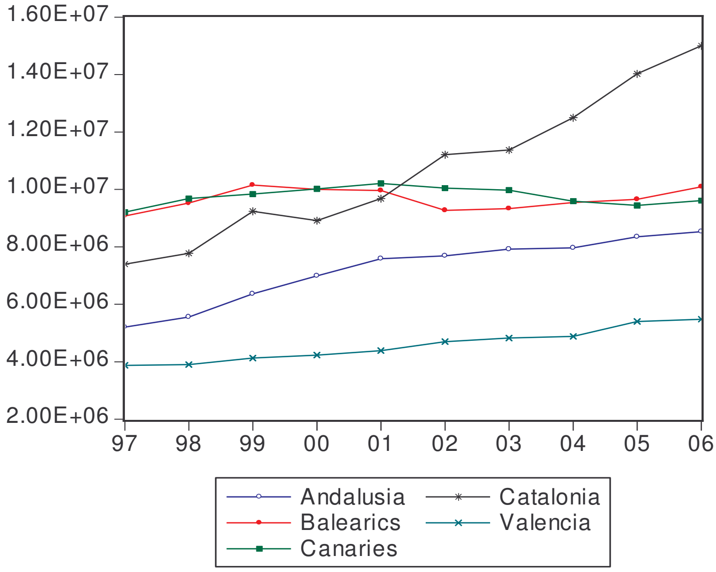


Table 1 provides the characteristics of tourism for the five major tourist regions in 2006. The first column in Table 1 gives the tourist/population ratio, which is the concentration of the number of tourists in relation to the number of inhabitants. Second, the number of international tourist arrivals and their share in the national level are given in columns 2 and 3, respectively. The next column presents a measure of seasonality, which is calculated using the Gini coefficient as a general measure of inequality. This is used in tourism to measure the difference in the number of tourists between seasons. In this case, the higher is the Gini coefficient, the higher is the inequality, that is, the difference between the high and low seasons (for further details, see Capó, Riera and Rosselló, 2007; Lundtorp, 2001; Rosselló, Riera and Sansó, 2004 and Tsitouras (2004)).

Table 1. Characteristics of the Main Spanish Tourist Regions in 2006

Region	Tourists/ Pop.	Tourist arrivals (millions)	% Spain	Gini[1]	Market specializ. (%)[2]	Two major sources	Average daily €
Andalusia	1	8.547	14.62	0.176	47.9	UK France	82
Balearics	10	10.107	17.29	0.373	73.4	Germany UK	95
Canaries	4	9.608	16.43	0.058	65.4	UK Germany	105
Catalonia	2.5	15.003	25.67	0.199	56	France UK	80
Valencia	1	5.485	9.38	0.168	59	UK France	63
Spain	**1.3**	**58.451**	**100**	**0.174**	**45.1**	**UK Germany**	**91**

Source of data: IET (2006a, 2006b)

[1] The degree of seasonality is defined using the Gini coefficient.
[2] Market Specialization is the % of international tourist arrivals from the two major source markets for each region.

In the fifth column of Table 1, the tourist country of origin is used to assess the market specialization of a tourist destination, in that a destination which attracts a greater number of tourist nationalities has a more diversified demand structure. The percentages shown in this column arise from the two major tourism source markets to the total tourist arrivals in each region, which are given in the second last column. For instance, in the case of the Balearics, 73.4% of total arrivals in 2006 originated from Germany and the UK, so that the Balearic Islands are the destination with the highest market specialization in Spain. In contrast, Spain has almost 55% of arrivals that originate from countries other than the two main markets of the UK and Germany, and hence has a higher market diversification, or a lower market specialization.

Finally, the average daily expenditure per tourist in Euro (€) is given in the last column in Table 1. It is clear that the tourism regions in which German and British tourist predominate, namely the Canaries, Balearics and the total of Spain, have the highest average daily expenditures. The three regions which are very similar to each other, namely Catalonia, Andalusia and Valencia, with France and the UK as the two major tourism source markets, have average daily expenditures that are reasonably close to each other.

Table 2. Tourism Impacts on Economic Variables in 2006 (%)

Region	GDP	Employment
Andalusia	12.1	11.1
Balearics	48.0	31.5
Canaries	30.4	36.8
Catalonia	12.0	12.1
Valencia	13.8	14.1
Total - Spain	**11.0**	**9.8**

Source: Exceltur (2007), INE (2007)

The direct and indirect tourism impact on economic variables in 2006 is described in Table 2. As a percentage of GDP in 2006, the tourism impact for Spain was 11%, which is only slightly lower than the respective percentages in Andalusia, Catalonia and Valencia, but considerably lower than in the Canaries at 30.4%, and particularly the Balearics at 48.0%. In terms of the percentage of employment generated by tourism, it is 9.8% for Spain, which is slightly lower than the respective percentages for Andalusia, Catalonia and Valencia, and considerably lower than in the Canaries and the Balearics, with 31.5% and 36.8%, respectively.

Using the data presented in Tables 1 and 2, in conjunction with Figure 9 which provides the geographical location, the remainder of Chapter 3 presents the main characteristics of tourism activity in the five major tourist regions of Spain.

Figure 9. Map of Spain

3.2.1 Andalusia

Located in the south of mainland Spain, Andalusia has a population of almost 8 million (INE, 2007). In 2006, this region received over 8.5 million international tourists, such that the tourist/population ratio is approximately 1. Tourist arrivals represent 14.62% of the total for Spain. Based on the Gini coefficient of 0.176, Andalusia has high seasonality, although not as severe as in other Spanish regions (AEA, 2005). This seasonality is explained by the fact that its primary type of tourism is the traditional sun and sand product. The main source market is the UK with a share of 35.7% of international tourist arrivals, followed by France with 12.2%. These two source markets represent 47.9% of total arrivals to Andalusia. In spite of being highly concentrated, it is still the lowest within the five major tourism regions. In 2006, each tourist spent an average of 82 € per day, which is 9 € below the national average (see Table 1). The impact of tourism on GDP is 12.1%, which is slightly higher than the average for Spain. Tourism generates 11.1% of total regional employment (see Table 2).

3.2.2 Balearic Islands

The Balearic Islands are comprised of four Islands in the Mediterranean Sea on the east coast of the Spanish mainland. With a total population of just over 1 million people (INE, 2007), and with over 10 million international arrivals, the ratio presented in the first column of Table 1 is clearly highest for the Balearics. In fact, it is nearly 10 times higher than the national ratio. The islands are in second place in the total share of international tourist arrivals, with 17.29% of the total for Spain. The tourism activity in the region is affected by very high seasonality, with the highest gini coefficient as seen in Table 1. Furthermore, this destination is also highly dependent on the German (39.7%) and British (33.7%) markets. These two nationalities accounted for almost three- quarters of total international tourist arrivals (73.4%). The average tourist daily expenditure of 95€ is the second highest in Spain, and above the national average. Regarding the economic impact of tourism in the Balearics, the sector accounts for 48% of regional GDP, being the highest in Spain, and provides employment to 31.5% of the labour market (Exceltur, 2007).

3.2.3 Canary Islands

Seven islands comprise this Spanish region that is located in the Atlantic Sea, slightly more than 300km from the African continent and 1300 km from the Spanish mainland. With almost 2 million inhabitants, these islands receive over 9 million international tourists, 16.43% of the Spanish total. Consequently, for every local person, there are four tourists. The total number of international tourist arrivals in 2006 placed the Canary Islands in third position, and very close to the Balearics. Its location makes the islands a very attractive destination all year round due to the stable climate. Compared with the rest of Spain, the summer months of June to August are considered the low tourist season, and the winter months are the high season. Tourist arrivals are spread more evenly over the calendar year, so that it is the region with the lowest seasonality. The two major source markets are the UK (37.5%) and Germany (27.9%), so that the Canaries are second in market specialization with 65.4% of total international tourist arrivals originating from these two countries. The Canaries are the leaders in average daily expenditure. A tourist in this region in 2006 spent an average of 105 €

daily (see Table 1). The impact of tourism on GDP is 30.4%, which is far higher than the Spanish average. Additionally, tourism generates 36.8% of total regional employment (see Table 2).

3.2.4 Catalonia

Catalonia is located in the north-east of Spain, and on the southern border of France. With 15 million international tourist arrivals in 2006, Catalonia occupies the first place in the arrivals ranking, and third place in the tourist/population ratio, with 2.5 international tourists for every resident. Catalonia receives 25.67% of international tourist arrivals to Spain and, since 2001, has occupied the first position in the number of international tourist arrivals. Catalonia also experiences seasonality, having a higher Gini coefficient than the national value, namely 0.199 versus 0.174, and is second in the tourism arrivals ratio. France is the major source market with 32.6%, followed distantly by the UK with 14.2%, which means that 56% of its tourism depends on these two originating markets. The average daily expenditure is below the national level, with 80 € per day. As in the case of Andalusia and the total for Spain, tourism accounts for 12% of GDP and 12.1% of employment.

3.2.5 Valencia

South of Catalonia and with a long coastline facing the Mediterranean, Valencia has a population of 4.8 million people. In 2006, this region received 5.5 million tourists, giving a tourist/population ratio of 1.1, which is just below the national ratio. With a 9.38% share of total international tourist arrivals, it occupies the last position of the five major tourism regions. The seasonality ratio is close to the national level, and is only slightly lower than the Andalusian Gini coefficient. It is highly specialized on the UK market, with 47.1%, and is followed distantly by the French market, with 11.9%. These two markets have a concentration of 59% of international tourist arrivals. Valencia has the lowest average daily expenditure per tourist, 63 €, which is close to 50% lower than the national level. Tourism accounts for 13.8% of GDP and 14.1% of employment.

3.2.6 Rest of Spain

In 2006, the rest of Spain received a total of 9.7 million international tourists. Madrid, the capital of Spain, with 3.9 million arrivals (or 6.7% of the total), is the region with the highest annual growth rate of all the Spanish regions (namely, 14.7% in 2006). The main difference from the five main tourism regions is that Madrid does not have a clear major source market, with the two major sources representing 25% of total international tourism arrivals to the region, while 36% of international tourism arrivals is business oriented (Dirección General Turismo, 2006). This explains why an international tourist in Madrid spends an average of 154 € daily, whereas the average for Spain is much lower at 90 € (IET, 2006a). These differences in the composition of tourists, as well as the significantly lower number of international tourists, justify why Madrid has not been included in the regional analysis. The rest of Spain receives a diversified demand by numerous countries of origin, in particular, with 24.6% originating from France and 17.5% from the UK.

3.3 Tourism in 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. During the year 2006 the Balearic Islands received, 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). Seasonality in tourism demand has been extensively studied in the literature. In the particular case of the Balearic Islands, this phenomenon has been studied by Capó, Riera and Roselló (2006) and by Rosselló, Riera and Sansó (2004). Additionally, 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 (Aguiló, Riera and Rosselló, 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 3). 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%, 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).

Table 3. 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

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, Aguiló, Alegre and Riera (2001) and Garin and Montero (2007) estimated price and income elasticities using yearly passenger arrivals data; Rosselló, Aguiló and Riera (2005) used a diffusion model to incorporate the word of mouth impact on tourism demand and calculated dynamic elasticities for German and British tourists and Aguiló, Riera and Rosselló (2005) calculated the effect of a tourist tax on the number of tourist arrivals using a diffusion model. 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 Rosselló, 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 (Aguiló, Alegre and Riera, 2001).

3.4 Conclusion

Based on 2006 data, Chapter 3 has given, firstly, a snapshot of the tourism industry in Spain. From the total international tourist arrivals to Spain, 83.4% stayed in one of the five major Spanish tourism regions of Andalusia, Balearic Islands, Canary Islands, Catalonia or Valencia. It is for this reason that these five regions have then been analysed and described from a tourism economics perspective. Secondly, this chapter has studied the economic significance of tourism to the three main islands of the Balearics, Mallorca, Ibiza and Menorca. Finally it has given the composition of tourism demand to the three different islands, and even though all three islands mainly cater for the standardized sun and sand tourism, there are significant differences between islands.

Chapter 4. MONTHLY INTERNATIONAL TOURIST ARRIVALS TO SPAIN

4.1 Introduction

This chapter describes the data of monthly international tourist arrivals to the five main Spanish tourist regions The data used for analyzing tourism in Spain has been obtained from the "Instituto de Estudios Tursíticos" (IET, 2006a, 2006b, 2007). This national institution analyzes the tourism industry in Spain and, through its website, publishes data gathered by "Frontur". Frontur denotes the statistical studies based on the use of periodic surveys completed at Spanish frontiers by a sample of international visitors. Thus, this Chapter is based on total international tourists who arrive by road, rail, sea or air. All domestic tourism is excluded from the sample.

4.2 An examination of monthly data

Frontur describes a visitor as any person arriving in a country other than the usual place of residence, for any reason apart following an occupation remunerated from within the country visited. An international tourist is a temporary visitor staying for at least 24 hours in the country visited, for which the purpose of the journey can be classified under the headings of either leisure or business, family, mission or meeting (IET, 2006a).

The data used are monthly international tourist arrivals to the five main tourist regions in Spain, which in 2006 accounted for more than 84% of total international tourist arrivals. The time period analyzed goes from January 1997 to April 2007, giving a total of 126 observations for each of the five regions, as well as the total for Spain.

Table 4 presents the correlations of international tourist arrivals among the five major tourist regions in Spain. The Canary Islands have negative correlations with the other four regions. This is quite natural because, as mentioned in Chapter 3, the Canary Islands high season months are the low season months for the rest of Spain, that is, from October to April. This would seem to suggest that the Canary Islands tourism smoothes, at least partly, the seasonality patterns for the other regions in Spain.

The highest correlations are found among Valencia, Andalusia and Catalonia. This is understandable as these three regions enjoy similar geographical characteristics, have long warm summers, and share more than 2,000 kilometers of coastline (INE, 2007). Additionally, they have well known tourist cities such as Barcelona, Valencia and Seville, which can smooth seasonality by attracting tourists during the low tourist season. The Balearic Islands have lower correlations, though they remain relatively high.

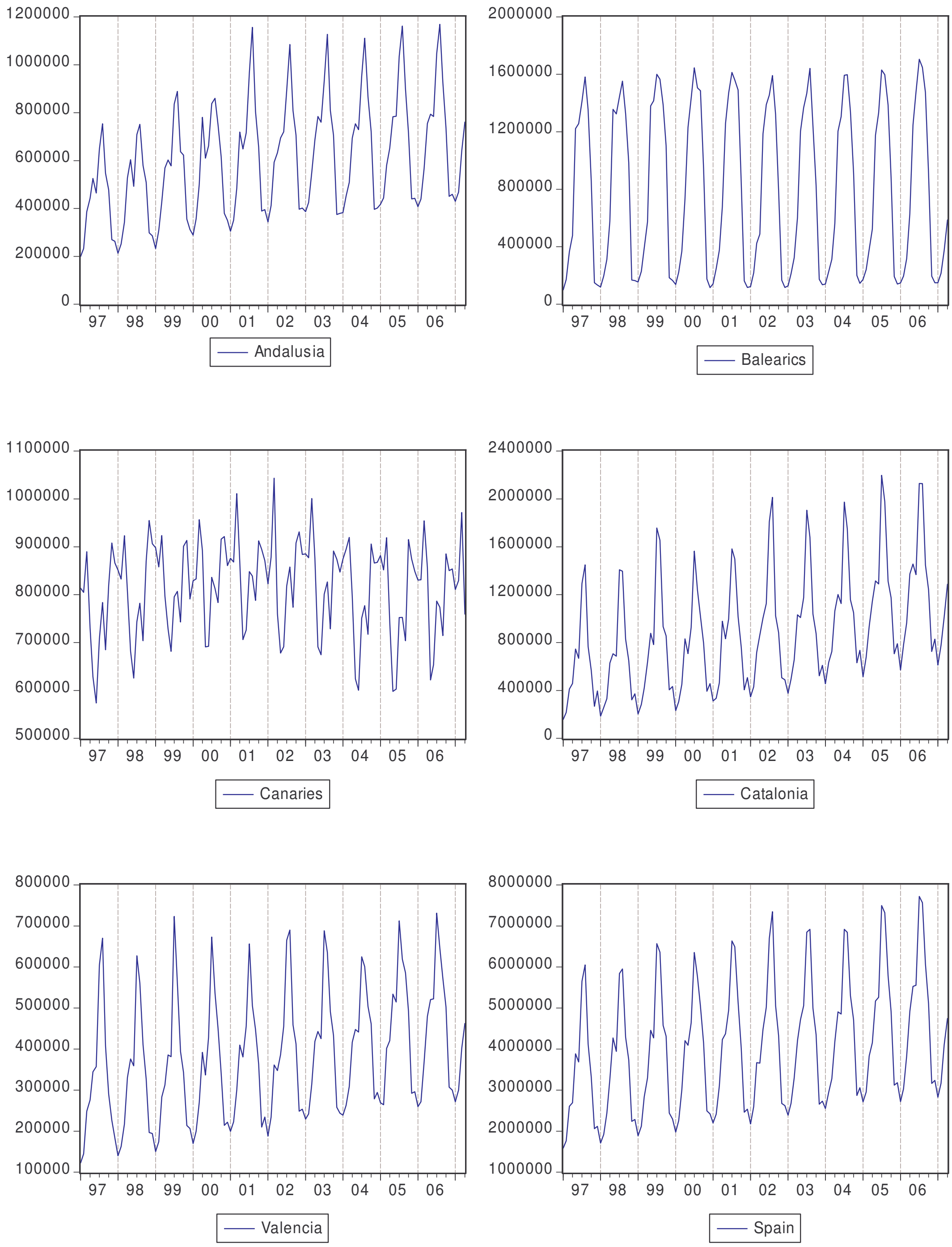
Table 4 Correlations of International Tourist Arrivals

Region	Andalusia	Balearics	Canaries	Catalonia	Valencia
Andalusia	1.000				
Balearics	0.850	1.000			
Canaries	-0.362	-0.618	1.000		
Catalonia	0.938	0.805	-0.369	1.000	
Valencia	0.931	0.869	-0.395	0.964	1.000

Figure 10 plots the monthly international tourist arrivals to each region and the total for Spain. In all graphs, the seasonal patterns are clearly identified. The Balearic

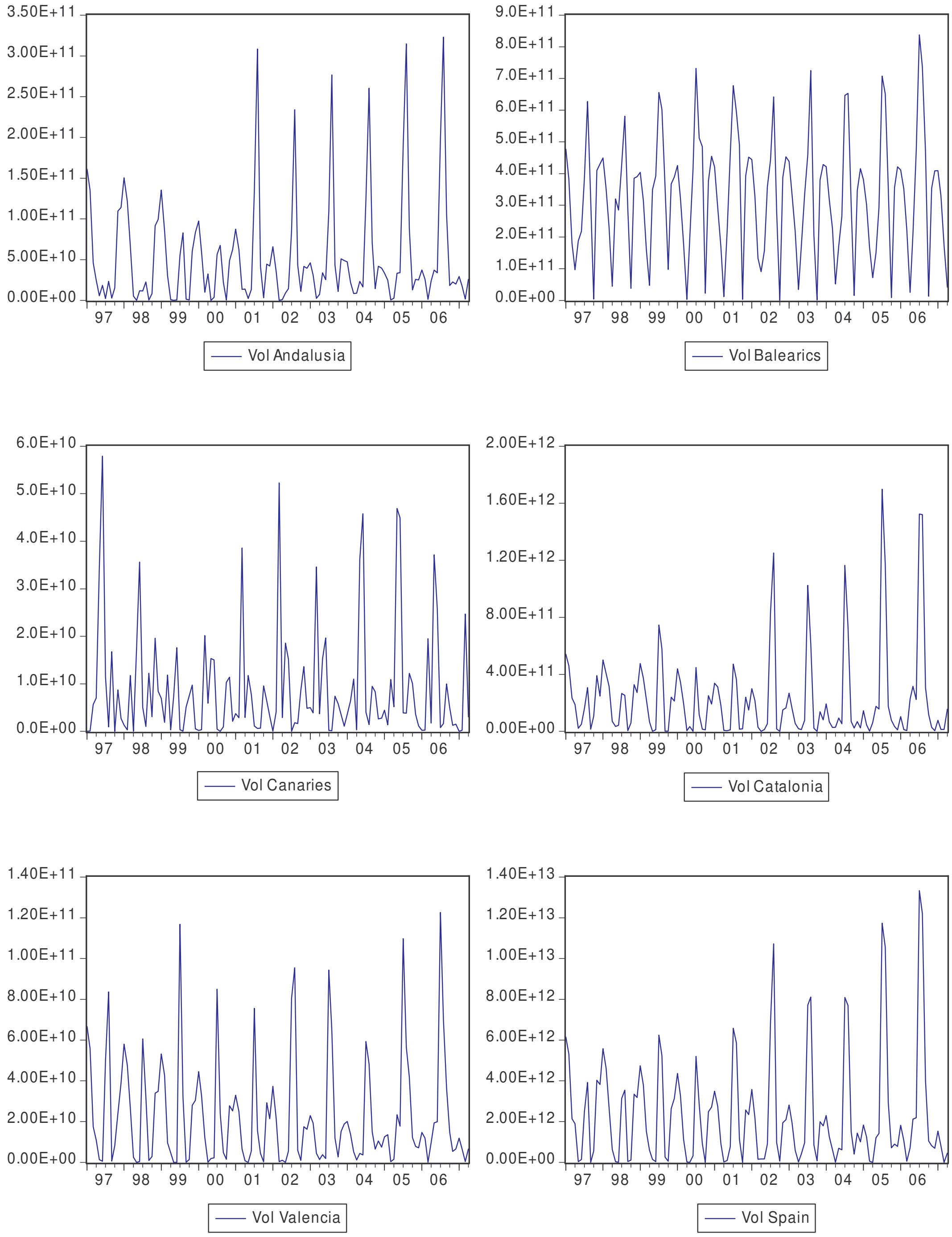
Islands appear to have the highest seasonality, in that the difference in monthly international tourist arrivals between the low and high seasons is the highest. Valencia, Andalusia and Catalonia seem to have a growing number of arrivals during the low tourist season. For Catalonia, the Christmas peak is clearly identified, most likely due to the attraction of popular skiing resorts. As expected, the Canary Islands follow a different seasonal pattern. After a few years of declining international tourist arrivals, the arrivals seem to have recovered since 2005.

Figure 10. Monthly International Tourist Arrivals



In Figure 11 are presented the volatility of monthly international tourist arrivals that are given in Figure 10. The seasonal pattern that was evident in the arrival series is repeated clearly and consistently in the associated volatility series.

Figure 11. Volatility of Monthly International Tourist Arrivals



Given the distinct seasonal patterns in both monthly international tourist arrivals and their associated volatilities, it would seem sensible to consider the twelve month (that is, yearly) difference in the monthly series. The yearly difference in international tourist arrivals and their associated volatilities are given in Figures 12 and 13, respectively. It is clear from the yearly difference series in Figure 12 that the distinct seasonal patterns that were evident in Figure 10 have now disappeared, so that the series would appear to exhibit stationary behavior at the zero (or non-seasonal) frequency. The null hypothesis of non-stationarity will be tested for Spain and for each of the five major tourist regions in section 4.4.

Figure 12. Yearly Difference in International Tourist Arrivals (Δ_{12} Y_t)

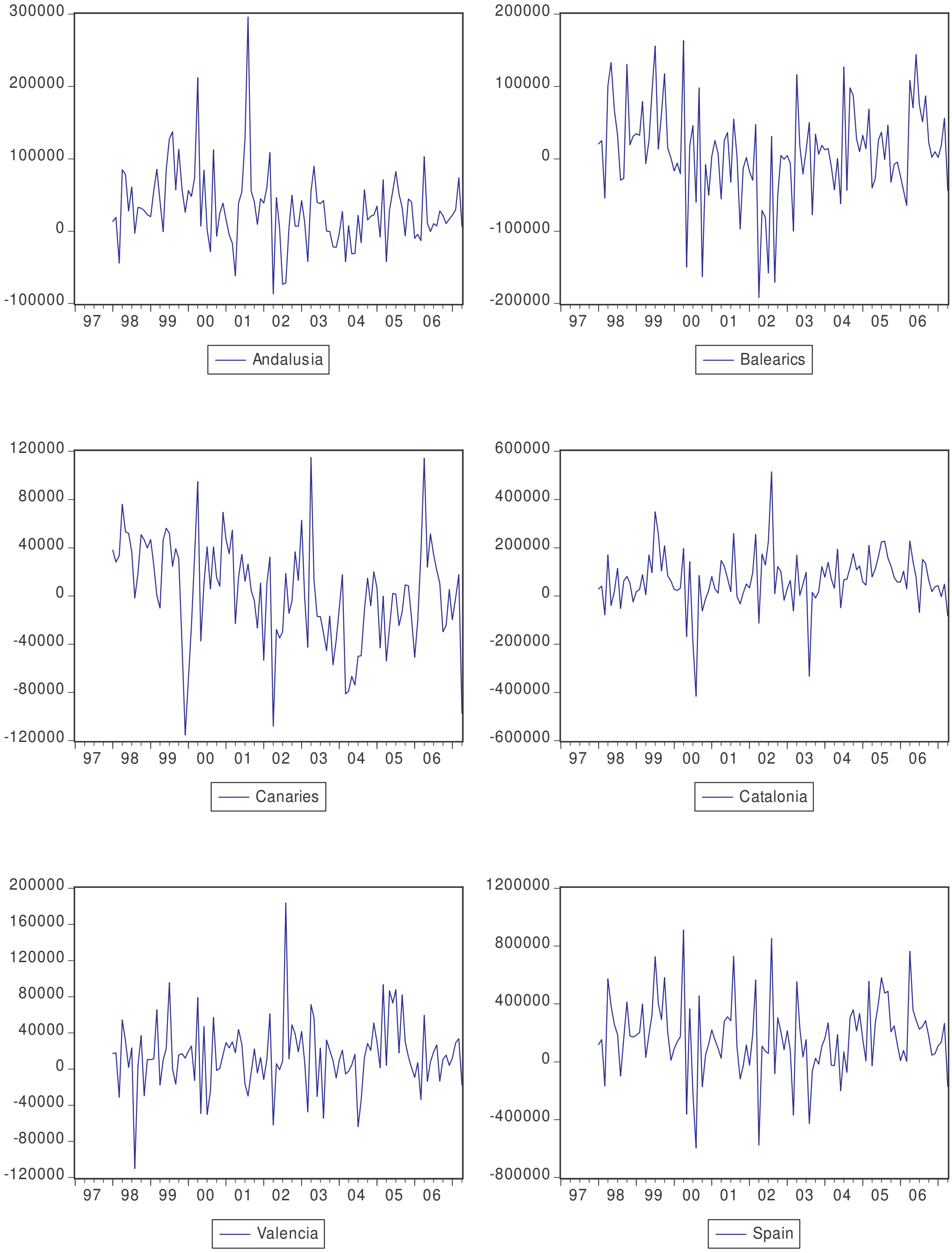
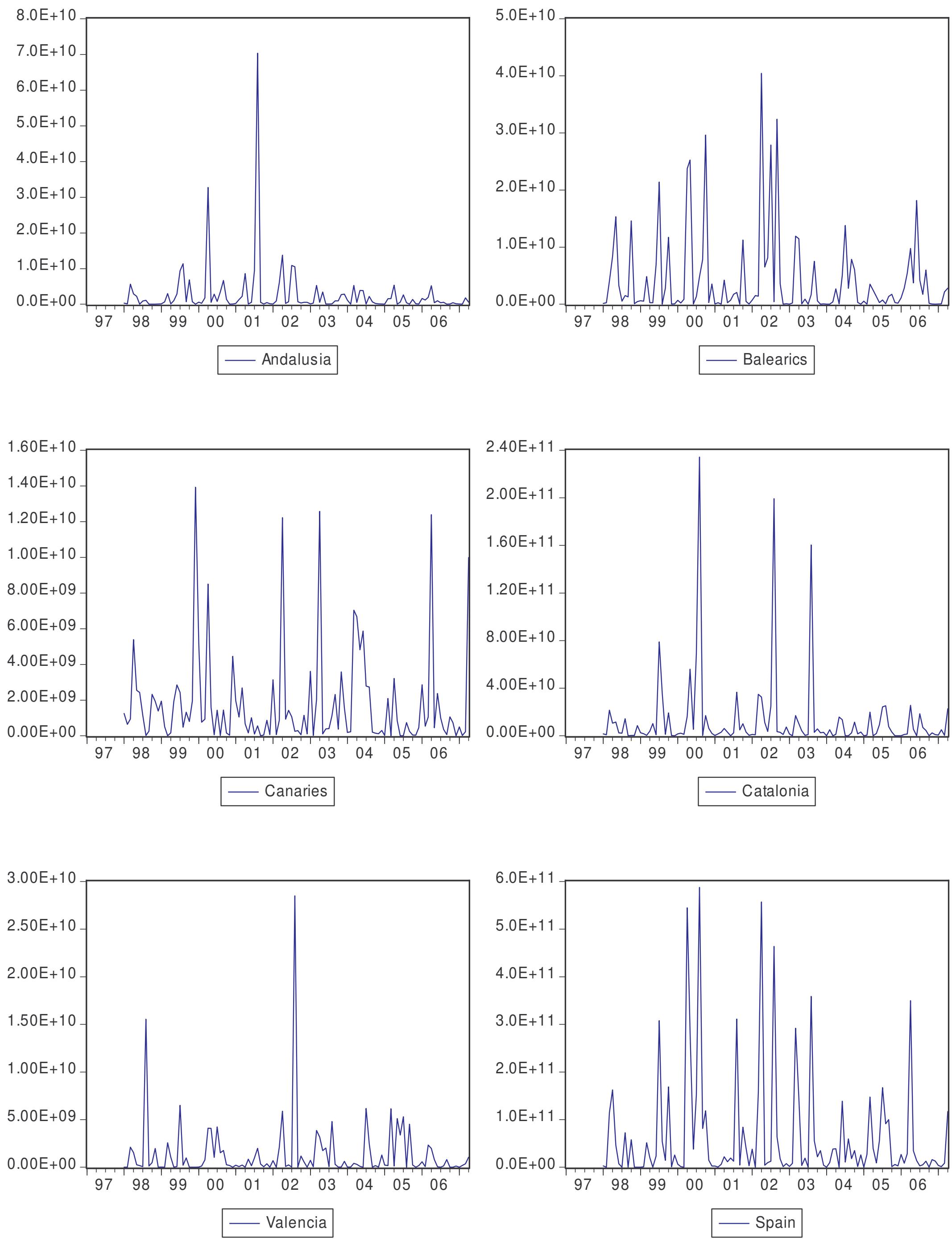


Figure 13. Volatility of Yearly Difference in International Tourist Arrivals



As the yearly differences in international tourist arrivals in Figure 12 do not display any distinct seasonal patterns, the associated volatilities given in Figure 13 also do not have any obvious seasonality. Indeed, the volatility evident in some of the graphs in Figure 12 appears to be reasonably similar to the volatility associated with typical financial time series data.

4.3 Descriptive statistics of the data

This section provides the descriptive statistics of monthly international tourist arrivals to the five main Spanish tourist regions as well as for the total of Spain, which are found in Table 5 below.

Table 5. Descriptive Statistics of Monthly International Tourist Arrivals to Spain

	Andalucía	Balearics	Canaries	Catalonia	Valencia	Spain
Mean	600,634.5	789,932.1	814,504.2	893,746.6	381,131.2	4,069,995.
Median	586,395	655,469	830,783.5	792,095.5	362,386.5	4,059,626.
Maximum	1,168,904.	1,705,234.	1,043,074.	2,196,544.	731,350.0	7,720,757.
Minimum	199,589	99,415	573,836	158,206	123,047.0	1,590,059.
Std. Dev.	232,660.7	574,228	96,301.1	484,163.7	152,512.1	1,548,462
Skewness	0.46	0.16	-0.41	0.75	0.50	0.50
Kurtosis	2.57	1.34	2.71	2.96	2.38	2.35
Jarque-Bera	5.34	14.76	3.96	11.87	7.23	7.40
Probability	0.069	0.000	0.137	0.003	0.027	0.025

With the exception of Catalonia, the Median is smaller than the mean in all samples. Given the previous analysis of seasonality, it is not surprising that the Balearics have the greatest standard deviation and the Canary Islands the smallest. All samples are positively skewed with the only exception of the Canaries sample. Catalonia and Canaries have kurtosis values near to three while the Balearics sample has a platykurtic distribution 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. The samples for Catalonia and Andalusia are found to be normally distributed.

4.4 Unit root test

This section tests the existence of a zero frequency unit root for the data. The modified unit root tests, denoted as $MADF^{GLS}$ and MPP^{GLS}, have been applied to the time series. 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).

The modified unit root tests, denoted as $MADF^{GLS}$ and MPP^{GLS}, have been applied to the time series data. 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 6, 7, 8 and 9. The existence of a zero frequency unit root is tested for monthly international tourist arrivals, first difference in arrivals, annual difference in arrivals, logarithm of arrivals, first difference in the log of arrivals, and the annual differences in the log of arrivals (that is, the annual growth rate) for the five regions and for Spain.

Table 6. Unit Root Tests for Spain

Variables	$MADF^{GLS}$ Z=(1, t)	$MADF^{GLS}$ Z=(1)	MPP^{GLS} Z=(1, t)	MPP^{GLS} Z=(1)	Lags
y_t	-3.498**	6.117	0.046	0.526	11
Δy_t	-1.039	-0.461	0.138	0.102	12
$\Delta_{12} y_t$	-4.041***	-3.936***	28.443***	-24.955***	4
$\log(y_t)$	-2.622	6.730	0.045	0.668	12
$\Delta\log(y_t)$	-1.856	-0.158	0.164	0.021	12
$\Delta_{12}\log(y_t)$	-4.051***	-3.528***	-24.805***	-15.265***	4

Notes:

y_t denotes monthly international tourist arrivals to Spain.

Δy_t is the difference in monthly international tourist arrivals to Spain.

$\Delta_{12} y_t$ is the yearly difference in monthly international tourist arrivals to Spain

$\log(y_t)$ is the logarithm of monthly international tourist arrivals to the Spain.

$\Delta\log(y_t)$ is the growth rate in monthly international tourist arrivals to Spain

$\Delta_{12}\log(y_t)$ is the yearly growth rate in monthly international tourist arrivals to Spain

(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% levels, respectively.

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

Table 7. Unit Root Tests for Andalusia

Variables	MADF^GLS		MPP^GLS		Lags
	Z=(1, t)	Z=(1)	Z=(1, t)	Z=(1)	
y_t	-1.139	2.932	-0.023	0.714	12
Δy_t	-1.192	-0.647	0.199	0.148	12
$\Delta_{12} y_t$	-8.078***	-7.793***	-51.858***	-50.880***	0
$\log(y_t)$	-1.324	3.228	-0.012	0.782	12
$\Delta\log(y_t)$	-2.138	-0.238	0.221	0.003	12
$\Delta_{12}\log(y_t)$	-8.553***	-4.018***	-53.240***	-21.592***	(0-2)[a]

Note: See notes to Table 6.

Table 8. Unit Root Tests for Balearic Islands

Variables	MADF^GLS		MPP^GLS		Lags
	Z=(1, t)	Z=(1)	Z=(1, t)	Z=(1)	
y_t	-2.969*	1.112	0.144	0.062	12
Δy_t	-1.389	-0.288	0.162	0.093	12
$\Delta_{12} y_t$	-3.831***	-3.851***	-16.934***	-16.721***	2
$\log(y_t)$	-2.577	0.999	0.023	0.334	12
$\Delta\log(y_t)$	-3.878***	0.041	0.343	-0.001	12
$\Delta_{12}\log(y_t)$	-1.098	-0.665	-2.653	-0.346	12

Note: See notes to Table 6.

Table 9. Unit Root Tests for Canary Islands

Variables	$MADF^{GLS}$ Z=(1, t)	$MADF^{GLS}$ Z=(1)	MPP^{GLS} Z=(1, t)	MPP^{GLS} Z=(1)	Lags
y_t	-1.704	-1.564	-0.282	-0.240	12
Δy_t	0.251	-1.103	1.432	1.937	12
$\Delta_{12} y_t$	-3.524**	-2.261**	-26.252***	-7.514*	4
$\log(y_t)$	-1.880	-1.673*	-0.365	-0.291	12
$\Delta \log(y_t)$	0.137	-1.129	1.226	1.640	12
$\Delta_{12} \log(y_t)$	-3.525**	-2.361**	-26.165***	-8.812**	4

Note: See notes to Table 6.

Table 10. Unit Root Tests for Catalonia

Variables	$MADF^{GLS}$ Z=(1, t)	$MADF^{GLS}$ Z=(1)	MPP^{GLS} Z=(1, t)	MPP^{GLS} Z=(1)	Lags
y_t	-3.168**	5.442	-0.025	0.819	11
Δy_t	-0.770	-0.562	0.200	0.179	12
$\Delta_{12} y_t$	-4.202***	-3.866***	-36.083***	-27.825***	3
$\log(y_t)$	-2.912*	6.938	0.032	0.857	11
$\Delta \log(y_t)$	-2.694	-0.018	0.231	-0.014	12
$\Delta_{12} \log(y_t)$	-3.787***	-3.226***	-19.733***	-10.722**	2

Note: See notes to Table 6.

Table 11. Unit Root Tests for Valencia

Variables	MADF^{GLS}		MPP^{GLS}		Lags
	Z=(1, t)	Z=(1)	Z=(1, t)	Z=(1)	
y_t	-3.754***	3.796	0.010	0.598	12
Δy_t	-1.416	-0.601	0.0863	0.047	12
$\Delta_{12} y_t$	-4.430***	-4.702***	-3.923	-2.370	11
$\log(y_t)$	-3.495**	5.095	0.046	0.717	12
$\Delta \log(y_t)$	-2.137	-0.177	0.140	-0.016	12
$\Delta_{12} \log(y_t)$	-2.550	-1.455	-15.187**	-1.752	12

Note: See notes to Table 6.

Apart from a few exceptions, the results of the unit root tests are remarkably similar. For a variety of lag lengths, monthly international tourist arrivals, the difference in monthly international tourist arrivals, the logarithm of monthly international tourist arrivals and the growth rate in monthly international tourist arrivals are all found to be non-stationary, that is, integrated of order one. The yearly difference in monthly international tourist arrivals and the yearly growth rate in monthly international tourist arrivals are both found to be stationary, that is, integrated of order zero. For these reasons, models of both monthly international tourist arrivals and the yearly growth rate in monthly international tourist arrivals, as well as their associated volatilities, will be estimated by maximum likelihood methods.

4.5 Estimated models

Models A1 and A2 below are used to estimate monthly international tourist arrivals and the yearly difference in monthly tourist arrivals, as well as their respective volatilities using the GARCH(1,1), GJR(1,1) and EGARCH(1,1) specifications:

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Model A2: $\Delta_{12} y_t = \phi_0 + \phi_1 \Delta_{12} y_{t-1} + \varepsilon_t$

The QMLE for the conditional mean and conditional volatility for Model 1 for Spain, as well as the five major tourist regions, are given in Tables 12-17. The corresponding QMLE for Model 2 are given in Tables 18-23.

Model A1

The conditional mean estimates for Model A1 for Spain in Table 12 suggest that international tourist arrivals lagged one month do not have a significant effect on current monthly arrivals, while international tourist arrivals lagged twelve months (that is, the yearly lagged effect) is highly significant. The asymmetric effect, γ, in both the GJR and EGARCH models is found to be zero, so that the effects of positive and negative shocks of equal magnitude on volatility are equivalent. The short run persistence of shocks in the GARCH model is not significant at 0.05, while the long run persistence shocks is 0.892. The second moment condition for both GARCH and GJR is satisfied, and hence the log-moment condition is also satisfied. Therefore, the QMLE are consistent and asymptotically normal, the estimates are sensible, and inferences are valid.

Table 12. Conditional Mean and Conditional Volatility Models for Spain

$$\text{Model A1: } y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	142915 (86429)	144333 (67867)	105737* (65168)
ϕ_1	0.021* (0.031)	0.018* (0.027)	0.021* (0.020)
ϕ_2	0.986 (0.034)	0.990 (0.029)	0.996 (0.026)
ω	7.35E+9* (1.73E+10)	9.12E+08* (5.30E+09)	31.501 (0.273)
GARCH/GJR α	0.005* (0.034)	0.046 (0.010)	--
GJR γ	--	-0.079* (0.045)	--
GARCH/GJR β	0.886 (0.270)	0.981 (0.094)	--
EGARCH α	--	--	0.401 (0.180)
EGARCH γ	--	--	-0.028* (0.164)
EGARCH β	--	--	-0.278 (0.000)
Diagnostics			
Second moment	0.892	0.988	--
Log-moment	-0.114	-0.013	--

Notes:
y_t is the number of monthly international tourist arrivals.
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.

The estimates of Model A1 for Andalusia are given in Table 13. A similar comment to that for Spain holds regarding the impact of international tourist arrivals lagged one month and one year. The asymmetry effect for both GJR and EGARCH are found to be significant, with the estimates for EGARCH suggesting Type 2 Asymmetry associated with overbooking pressure on carrying capacity. Unlike the estimates for

Spain, the short run persistence of shocks for Andalusia is very high and not significantly different from unity for both GARCH and GJR. As the log-moment condition is satisfied in both cases, he estimates are sensible and any inferences drawn will be valid.

Table 13. Conditional Mean and Conditional Volatility Models for Andalusia

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	25631 (12080)	27891 (12870)	28802 (5412)
ϕ_1	0.033* (0.028)	0.046* (0.027)	0.041 (0.020)
ϕ_2	0.958 (0.028)	0.945 (0.027)	0.950 (0.022)
ω	8.90E8 (2.56E+8)	1.08E+9 (2.87E+8)	16.380 (3.068)
GARCH/GJR α	0.983 (0.234)	1.252 (0.369)	--
GJR γ	--	-1.022 (0.453)	--
GARCH/GJR β	0.017* (0.051)	0.007* (0.033)	--
EGARCH α	--	--	1.020 (0.219)
EGARCH γ	--	--	0.320 (0.163)
EGARCH β	--	--	0.196* (0.142)
Diagnostics			
Second moment	1.000	0.749	--
Log-moment	-1.207	-1.756	--

Notes: See Table 10

The estimates for the Balearic Islands in Table 14 are reasonably similar to those for Spain in that the asymmetric effects are not significant for GJR or EGARCH. However the short run persistence of shocks for the GARCH model is significant at 0.534, which is far higher than for Spain and much lower than for Andalusia. However, like the two previous sets of results, the log-moment condition is satisfied for both

GARCH and GJR, so that the QMLE are consistent and asymptotically normal, and the estimates are sensible.

Table 14. Conditional Mean and Conditional Volatility Models for Balearic Islands

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	3712* (10745)	3740* (11170)	3690* (7237)
ϕ_1	0.013* (0.019)	0.013* (0.019)	0.009* (0.014)
ϕ_2	0.993 (0.027)	0.993 (0.027)	0.996 (0.013)
ω	2.08E+9 (4.76E+8)	2.08E+9 (5.15E+8)	31.379 (3.359)
GARCH/GJR α	0.534 (0.237)	0.538* (0.290)	--
GJR γ	--	-0.009* (0.463)	--
GARCH/GJR β	0.123* (0.104)	0.122* (0.126)	--
EGARCH α	--	--	0.839 (0.154)
EGARCH γ	--	--	0.065* (0.071)
EGARCH β	--	--	-0.450 (0.148)
Diagnostics			
Second moment	0.657	0.656	--
Log-moment	-1.027	-1.029	--

Notes: See Table 10

The conditional mean estimates for Model A1 for the Canary Islands in Table 15 are very similar to the four previous cases, except that the effect of the yearly lag is much lower at between 0.805 and 0.883. As in the case of Spain and the Balearic Islands, the asymmetric effects are not significant for GJR or EGARCH. The short run persistence of shocks for GARCH is positive but not significant. Overall, the QMLE for the Canaries do not seem to be particularly intuitive.

Table 15. Conditional Mean and Conditional Volatility Models for Canary Islands

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	97438 (39779)	91976 (30705)	76892 (30837)
ϕ_1	0.047* (0.041)	0.085 (0.035)	0.024* (0.039)
ϕ_2	0.836 (0.048)	0.805 (0.038)	0.883 (0.038)
ω	2.70E+9 (6.24E+8)	2.79E+9 (4.92E+9)	33.391 (3.953)
GARCH/GJR α	0.170* (0.095)	0.263 (0.106)	--
GJR γ	--	-0.149* (0.130)	--
GARCH/GJR β	-0.786 (0.202)	-0.852 (0.117)	--
EGARCH α	--	--	0.656 (0.223)
EGARCH γ	--	--	0.136* (0.130)
EGARCH β	--	--	-0.606 (0.179)
Diagnostics			
Second moment	-0.616	-0.663	--
Log-moment	NA	NA	--

Notes: See Table 10
NA denotes not available

Both the conditional mean and conditional volatility estimates for Catalonia are presented in Table 16. The impact of international tourist arrivals lagged one month and one year are very similar to the previous four sets of results. As in the case of all previous results except for Andalusia, the asymmetric effects of positive and negative shocks are insignificant. The short run persistence of shocks for GARCH is positive and similar to that of the Balearic Islands at 0.487. As both the second moment and log moment conditions are satisfied, the estimates are sensible and standard statistical analysis is valid.

Table 16. Conditional Mean and Conditional Volatility Models for Catalonia

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	52727 (26634)	56117 (25909)	73132 (16065)
ϕ_1	0.053* (0.030)	0.052* (0.033)	0.016* (0.017)
ϕ_2	0.955 (0.022)	0.954 (0.024)	0.975 (0.017)
ω	7.91E+9 (2.26E+9)	7.53E+9 (2.20E+9)	35.699 (1.853)
GARCH/GJR α	0.487 (0.147)	0.745 (0.365)	--
GJR γ	--	-0.396* (0.391)	--
GARCH/GJR β	0.015* (0.157)	0.011* (0.135)	--
EGARCH α	--	--	0.982 (0.162)
EGARCH γ	--	--	-0.030* (0.103)
EGARCH β	--	--	-0.576 (0.077)
Diagnostics			
Second moment	0.502	0.559	--
Log-moment	-1.957	-1.967	--

Notes:See Table 10.

Estimates of the conditional mean and conditional volatility for Valencia are presented in Table 17. A similar comment to the previous five sets of results applies to the impact of international tourist arrivals lagged one month and one year. Although the asymmetric effect in the GJR model is not significant the asymmetric effect for EGARCH displays Type 3 Asymmetry, namely tourism saturation in the high season. As the short and long run persistence for GARCH are not intuitive, even though the QMLE are consistent and asymptotically normal, the EGARCH model is preferred.

Table 17. Conditional Mean and Conditional Volatility Models for Valencia

Model A1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-12} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	29454.39 (8995.98)	22178.93* (14888.56)	9640.96 (3480.85)
ϕ_1	0.011* (0.018)	0.062* (0.032)	0.140 (0.024)
ϕ_2	0.944 (0.026)	0.919 (0.039)	0.872 (0.022)
ω	1.02E+8 (7676109)	6.07E+8* (7.69E+8)	9.485 (0.763)
GARCH/GJR α	-0.101 (0.008)	-0.061 (0.002)	--
GJR γ	--	-0.058* (0.147)	--
GARCH/GJR β	1.041 (0.003)	0.696* (0.463)	--
EGARCH α	--	--	-0.507 (0.103)
EGARCH γ	--	--	0.618 (0.089)
EGARCH β	--	--	0.566 (0.035)
Diagnostics			
Second moment	0.940	0.606	--
Log-moment	-0.129	NA	--

Notes: See Table 10.
NA denotes not available

As a summary of the results presented for the conditional variance applying model 1, the estimates obtained from the aggregate tourist arrivals to Spain are different from those obtained from each of the five main tourist regions. In particular, in the GARCH model estimates the short run effect of the shocks (α) is not significant for the aggregate sample, while it is significant for four of the five regions and with very different values. These differences derive from alternative geographical aggregation are also found in the EGARCH size effects.

Model A2

The next paragraphs present the results corresponding to the empirical analysis of Model 2 for the five main tourist regions of Spain and the aggregate. The conditional mean estimates for Spain in Table 18 suggest that the yearly international tourist arrivals lagged one month in Model A2 do not have a significant effect on the yearly change in monthly international tourist arrivals. The asymmetric effects for both GJR and EGARCH are insignificant. The short run persistence of shocks for GARCH is insignificant, so that the EGARCH model is preferred.

Table 18. Conditional Mean and Conditional Volatility Models for Spain

Model A2: $\Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}\, y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	145071 (30285)	171088 (12173)	173409 (33004)
ϕ_1	0.121* (0.116)	-0.012* (0.086)	0.031* (0.135)
ω	7.24E+10 (2.35E+10)	-2.01E+9* (8.78E+9)	31.906 (15.671)
GARCH/GJR α	0.279* (0.167)	0.020 (0.001)	--
GJR γ	--	-0.054* (0.029)	--
GARCH/GJR β	-0.294* (0.281)	1.039 (0.142)	--
EGARCH α	--	--	0.354* (0.191)
EGARCH γ	--	--	0.002* (0.137)
EGARCH β	--	--	-0.292* (0.629)
Diagnostics			
Second moment	-0.015	1.032	--
Log-moment	NA	NA	--

Notes:
$\Delta_{12}y_t$ is the yearly difference in monthly international tourist arrivals.
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.
NA denotes not available

Table 19 presents the estimates for Model A2 for Andalusia. The yearly international tourist arrivals lagged one month are significant at between 0.212 and 0.326. The asymmetric effects for both GJR and EGARCH are insignificant. The short run persistence of shocks for GARCH is significant at 0.475. As the second moment condition is satisfied, the QMLE are consistent and asymptotically normal, and any inferences based on the estimates are valid.

Table 19. Conditional Mean and Conditional Volatility Models for Andalusia

$$\text{Model A2: } \Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}\, y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	20545 (7421)	21378 (5079)	20610 (3877)
ϕ_1	0.326 (0.140)	0.252 (0.125)	0.212 (0.080)
ω	2.66E+9 (1.00E+9)	1.41E+9 (2.93E+8)	16.979 (2.963)
GARCH/GJR α	0.475 (0.177)	0.906 (0.273)	--
GJR γ	--	-0.608* (0.379)	--
GARCH/GJR β	-0.162* (0.219)	-0.034 (0.007)	--
EGARCH α	--	--	1.119 (0.208)
EGARCH γ	--	--	0.213* (0.154)
EGARCH β	--	--	0.166* (0.138)
Diagnostics			
Second moment	0.313	0.568	--
Log-moment	NA	NA	--

Notes: See Table 16

The estimates for the conditional mean and the conditional volatility for the Balearic Islands are presented in Table 20. The results are very similar to those for Andalusia in that the asymmetric effects are insignificant for both GJR and EGARCH. However, the short run persistence of shocks for GARCH is significant at higher value of 0.843. As the second moment and log-moment conditions are satisfied, the estimates are sensible and inferences are valid.

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

Model A2: $\Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}\, y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	5355* (4099)	6687* (5457)	6384* (5390)
ϕ_1	0.180* (0.117)	0.185* (0.103)	0.099* (0.093)
ω	2.16E+9 (5.61E+8)	2.28E+9 (5.92E+8)	30.028 (3.619)
GARCH/GJR α	0.843 (0.316)	1.021 (0.480)	--
GJR γ	--	-0.401* (0.638)	--
GARCH/GJR β	0.002* (0.091)	-0.016* (0.096)	--
EGARCH α	--	--	0.838 (0.154)
EGARCH γ	--	--	0.065* (0.071)
EGARCH β	--	--	-0.388 (0.160)
Diagnostics			
Second moment	0.845	0.804	--
Log-moment	-1.767	NA	--

Notes: See Table 16

As in the case of the conditional mean and conditional volatility models for Model 1 for the Canary Islands, the counterpart for Model 2 in Table 21 is slightly more intuitive. The asymmetric effects are insignificant for both GJR and EGARCH. The short run persistence of shocks for GARCH is not significant. Overall, the EGARCH model is preferred.

Table 21. Conditional Mean and Conditional Volatility Models for Canary Islands

Model A2: $\Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}\, y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	476.274* (4071)	2372* (3331)	865.052* (3219)
ϕ_1	0.471 (0.097)	0.426 (0.078)	0.444 (0.085)
ω	2.55E+9 (6.12E+8)	52693580 (23790687)	32.212 (3.915)
GARCH/GJR α	0.093* (0.078)	-0.037 (0.001)	--
GJR γ	--	-0.007* (0.025)	--
GARCH/GJR β	-0.801 (0.214)	1.011 (0.011)	--
EGARCH α	--	--	0.496 (0.220)
EGARCH γ	--	--	0.050* (0.131)
EGARCH β	--	--	-0.547 (0.184)
Diagnostics			
Second moment	-0.708	0.970	--
Log-moment	NA	NA	--

Notes: See Table 16

The estimates for Catalonia in Table 22 are quantitatively similar to those for Andalusia in Table 19. The yearly international tourist arrivals lagged one month lie between 0.073 and 0.245, but are not significant. The asymmetric effects for both GJR and EGARCH are insignificant. The short run persistence of shocks for GARCH is significant at 0.438. As the second moment condition is satisfied, the QMLE are consistent and asymptotically normal, and the estimates are sensible.

Table 22. Conditional Mean and Conditional Volatility Models for Catalonia

Model A2: $\Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	46636 (13612)	51676 (13176)	61461 (7062)
ϕ_1	0.222* (0.157)	0.245* (0.158)	0.073* (0.093)
ω	9.57E+9 (2.31E+9)	9.67E+9 (2.71E+9)	36.034 (2.454)
GARCH/GJR α	0.438 (0.172)	0.660 (0.283)	--
GJR γ	--	-0.375* (0.302)	--
GARCH/GJR β	-0.084* (0.181)	-0.115* (0.204)	--
EGARCH α	--	--	0.825 (0.146)
EGARCH γ	--	--	0.001* (0.067)
EGARCH β	--	--	-0.589 (0.106)
Diagnostics			
Second moment	0.354	0.227	--
Log-moment	NA	NA	--

Notes: See Table 16.

Finally, the estimates for Model 2 for Valencia are presented in Table 23. As in the case of Spain, the Balearic Islands and Catalonia, the yearly international tourist arrivals lagged one month are not significant for Valencia. The asymmetric effects for both GJR and EGARCH are insignificant. Moreover, none of the estimates for EGARCH is significant. As the second moment and log-moment conditions are satisfied for GARCH and GJR, the estimates are sensible and any associated inferences are valid.

Table 23. Conditional Mean and Conditional Volatility Models for Valencia

Model A2: $\Delta_{12}y_t = \phi_0 + \phi_1\Delta_{12}\, y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	15031.21 (3670.13)	14630.92 (3172.03)	15368.5 (3092.09)
ϕ_1	-0.016* (0.082)	-0.025* (0.072)	-0.053* (0.072)
ω	60688240 (8475898)	98930692 (7886501)	18.091* (10.263)
GARCH/GJR α	-0.064 (0.001)	-0.071 (0.017)	--
GJR γ	--	-0.027* (0.020)	--
GARCH/GJR β	1.026 (0.008)	1.023 (0.019)	--
EGARCH α	--	--	-0.319* (0.277)
EGARCH γ	--	--	0.157* (0.128)
EGARCH β	--	--	0.151* (0.480)
Diagnostics			
Second moment	0.963	0.938	--
Log-moment	-0.064	-0.107	

Notes: See Table 16

The general overview of the results presented for model 2 provide the same conclusions that the one obtained from model 1, indicating the differences in the estimated parameters obtained from the aggregate sample and for the regional samples.

Hence it seems that the information of the different shocks affecting different regions and its effect is partly lost in the aggregate figures.

4.6 Conclusion

As it is widely acknowledged that tourism is important economically, socially and culturally, an analysis of international tourism demand across and within countries is crucial for understanding its global and regional impact. Recent developments in the availability of data have provided opportunities for applying analytical tools that were originally designed for other disciplines. For purposes of a more detailed empirical analysis, there are now sources that provide data at the weekly and monthly frequencies.

The Chapter has analyzed monthly international tourist arrivals to the five main regions in Spain, which accounted for more than 84% of total international tourist arrivals, from January 1997 to April 2007, giving a total of 126 observations for each of the five regions, as well as for Spain. Given the distinct seasonal patterns in both monthly international tourist arrivals and their associated volatilities, twelve month (that is, yearly) differences in the monthly series were considered.

Univariate time series models are estimated for the conditional means of the monthly international tourist arrivals and annual changes in tourist arrivals, as well as their conditional volatilities, for the five main tourist regions, as well as for Spain. The estimated conditional volatility models were GARCH(1,1), GJR(1,1) and EGARCH(1,1). Both the second moment and log-moment conditions were calculated to provide diagnostic checks of the estimated models. Four different types of asymmetries relating to monthly international tourist arrivals were presented. Asymmetry type 3 was found in Valencia, which can be interpreted as tourism saturation during the high season, as positive shocks increase volatility or risk while negative shocks decrease it. The stationarity of the time series data was tested using modified unit root tests. The conditional mean estimates were generally statistically adequate, and the conditional volatility estimates were found to be meaningful, as well as consistent and asymptotically normal, so that inferences were valid.

These time series models also permitted different levels of spatial aggregation in order to shed light on the optimal political and regional size in the design of tourist policies for efficient tourism risk management and marketing. As seen, the estimates for the aggregated data for Spain provide different results than when data is disaggregated into the different regions. The ultimate objective is to obtain precise information regarding the degree of regional diversification of the tourism industry, which may help to reduce the economic and financial risks for the country as a whole.

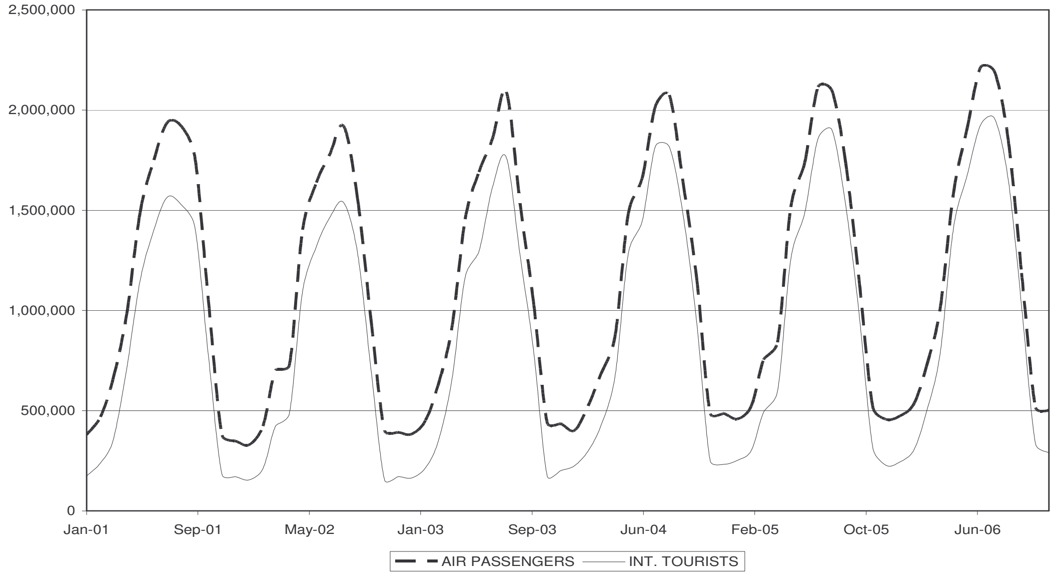
Chapter 5. DAILY AIR PASSENGER ARRIVALS TO THE BALEARIC ISLANDS

5.1 Introduction

This chapter analyzes daily air passenger arrivals between 2001 and 2006 to the three international airports of the Balearic Islands. As data on daily tourist arrivals are not available, total passenger arrivals data are used as a proxy to model international tourism demand. Daily data provide more detailed information, so that estimation will be more precise for purposes of modelling and forecasting international tourist arrivals. Furthermore, daily data are very useful for purposes of modelling the conditional variance of the time series when the assumption of constant variances is deemed to be unreasonable.

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 14 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.

Figure 14. International Tourist and Passenger Arrivals to the Balearic Islands



5.2 An examination of daily data

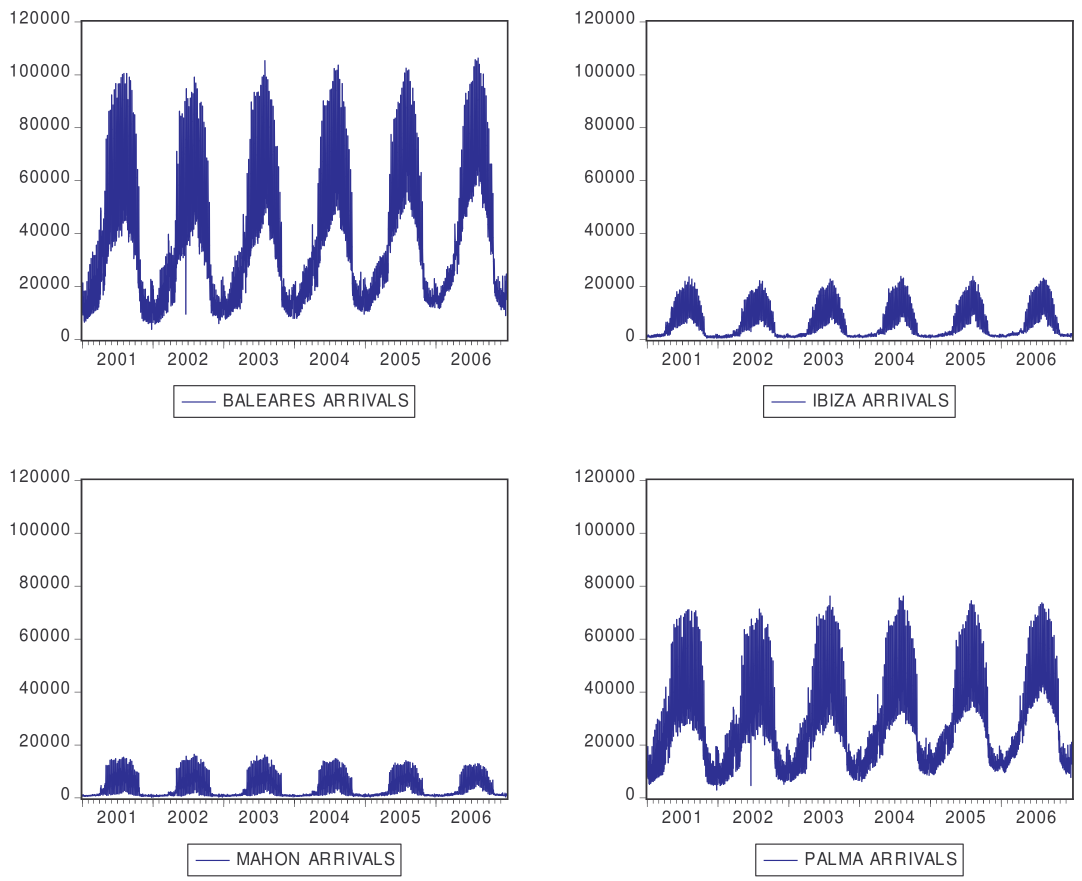
The data set comprises daily passenger arrivals at the three international airports in the Balearic Islands, namely Palma de Mallorca, Ibiza and Mahon, which are located in the islands of Mallorca, Ibiza and Menorca, respectively, with data for the Balearics being the aggregate of arrivals to the three 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 modelling and forecasting international tourist arrivals. Additionally, the findings will be useful for business planning and resource management, such as staffing and stock arrangement (Song *et al,*

2008) Furthermore, daily data are very useful for purposes of modelling the conditional variance of the time series when the assumption of constant variances is deemed to be unreasonable.

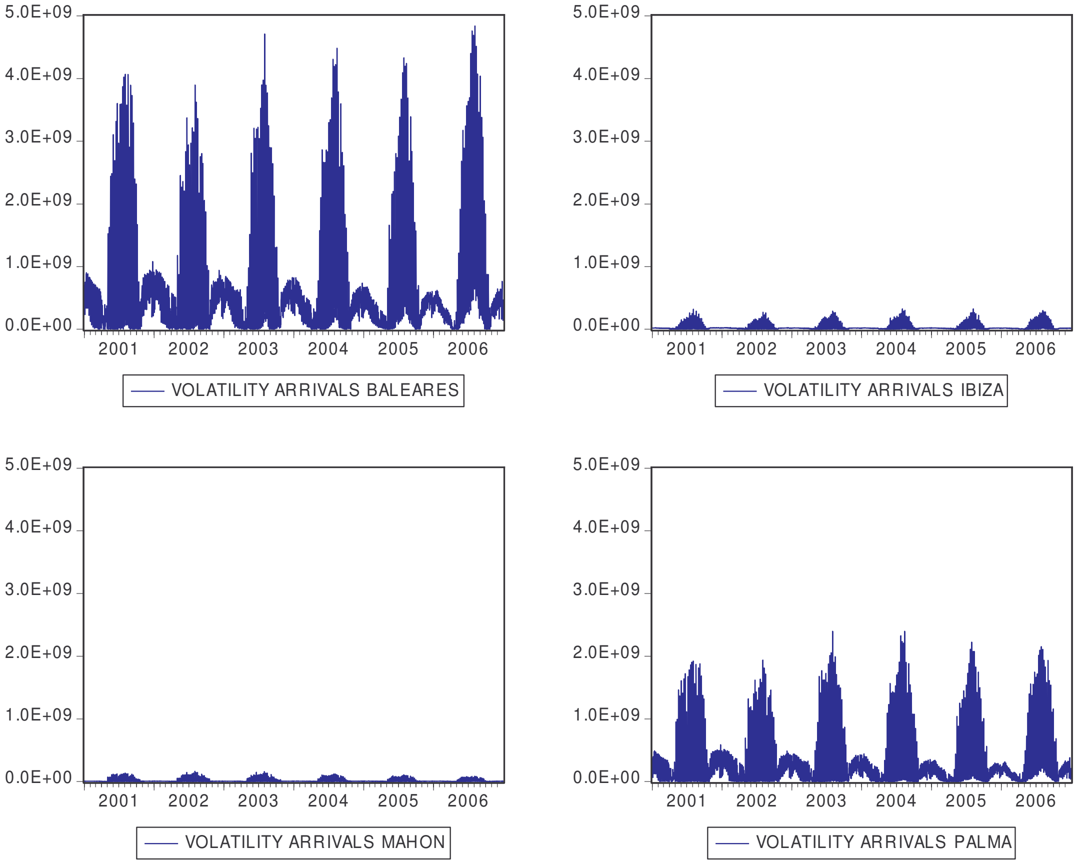
Figure 15 plots the daily air passenger arrivals for Mallorca, Menorca, Ibiza and the Balearics. Figure 16 plots the volatility of daily air passenger arrivals, where volatility is defined as the squared deviation from the sample mean.

Figure 15. Daily Passenger Arrivals



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.

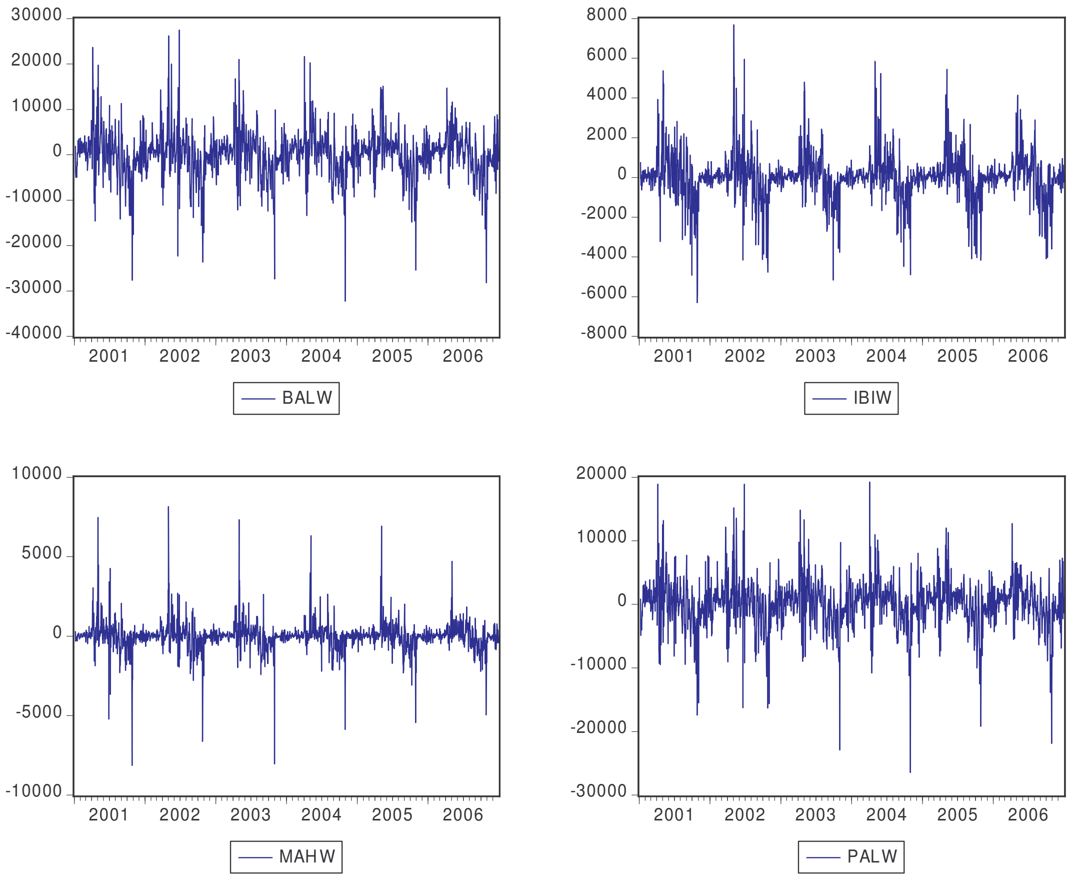
Figure 16. Volatility of Passenger Arrivals



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.

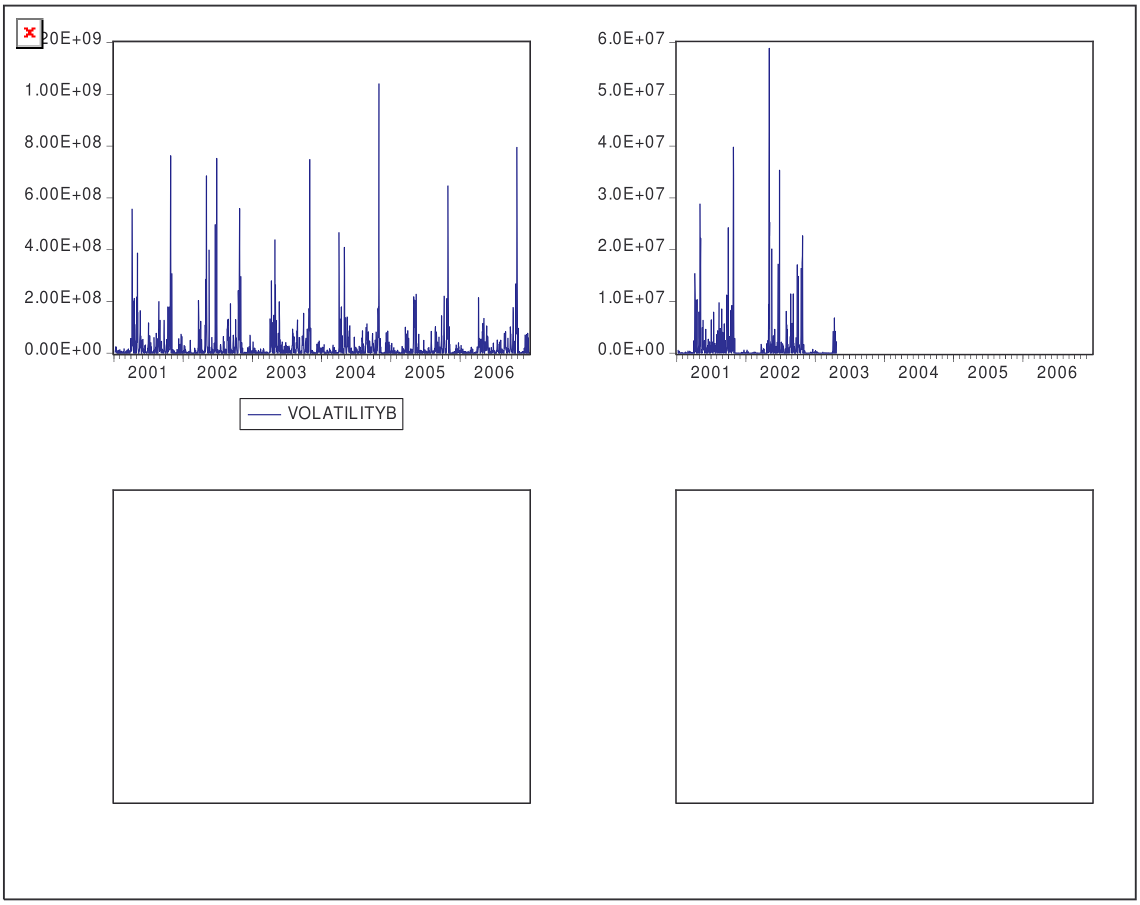
Figures 17 and 18 plot the weekly differences and the volatility, respectively, in daily air passenger arrivals for the four samples. A closer analysis of Figures 15 and 16 shows a weekly pattern in the data. Consequently, the weekly difference in passenger arrivals in Figure 17 and its volatility in Figure 18 seem to have eliminated the weekly pattern.

Figure 17. 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 18. 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.

5.3 Descriptive statistics of the data

Table 24 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.

Table 24. 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

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 25 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 is 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.

Table 25. 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

5.4 Unit root rests

Following the same methodoly described in section 4.4, the modified unit root tests, denoted as $MADF^{GLS}$ and MPP^{GLS}, have been applied to the time series data. In essence, these tests use GLS de-trended data and the modified Akaike information criterion (MAIC) to select the optimal truncation lag.

The results of the unit root tests are reported in Tables 26, 27, 28 and 29. The existence of a zero frequency unit root is tested for daily passenger arrivals and for the weekly difference for the sum of Balearic Islands and for the different islands of Ibibza, Menorca and Mallorca.

Table 26. 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 27. 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 28. 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 29. 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.

In Tables 26-29, the lags are all in the order of 20 to 25 days, which is roughly three weeks of daily data. In Table 24 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 27-29, 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, models for both series will be estimated, as well as their respective volatilities.

5.5 Estimated models

The following models are used to estimate passenger arrivals (Models B1 and B3) and the weekly differences in passenger arrivals (Models B2 and B4), as well as their respective volatilities using GARCH(1,1), GJR(1,1) and EGARCH(1,1):

Model B1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

Model B2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

Model B3: $y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$

Model B4: $\Delta_7 y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\mathrm{L}} \Delta_7 y_{t-7} + \varepsilon_t$

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:

$\delta_{\mathrm{H}} = 1$ ($\delta_{\mathrm{L}} = 0$) for the high tourist season, 1 April to 31 October;
$\delta_{\mathrm{H}} = 0$ ($\delta_{\mathrm{L}} = 1$) for the low tourist season, 1 November to 31 March.

Model B1 explains daily passenger arrivals to one destination as depending on passenger arrivals lagged 1 and 7 days, while Model B3 distinguishes between the high and low seasons in terms of explaining daily passenger arrivals. Model B2 explains the weekly differences in passenger arrivals as an autoregressive process of order 1, and Model B4 explains the change in weekly passenger arrivals as a restricted autoregressive process of order 7.

Models B3 and B4 enable an investigation of the differences between the high and low tourist seasons in terms of analyzing daily passenger arrivals and their weekly differences. 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.

Model B1

The conditional means and conditional volatilities of passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca are given for Model B1 in Tables 28-31, 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 44.

It is striking that the results in Tables 28-31 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 28 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.

Table 30. Conditional Mean and Conditional Volatility Models for the Balearic Islands

Model B1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

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.

Tables 29-31 give the estimates for Model B1 for Ibiza, Menorca and Mallorca, respectively. Overall, the results in these three tables are qualitatively similar to those in Table 28 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.

Table 31. Conditional Mean and Conditional Volatility Models for Ibiza

Model B1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

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 32. Conditional Mean and Conditional Volatility Models for Menorca

Model B1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

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 33. Conditional Mean and Conditional Volatility Models for Mallorca

Model B1: $y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-7} + \varepsilon_t$

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.

Model B2

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 B2 in Tables 32-35, respectively. In Table 32 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 33-35, 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.

Table 34. Conditional Mean and Conditional Volatility Models for the Balearic Islands

Model B2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

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 35. Conditional Mean and Conditional Volatility Models for Ibiza

Model B2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

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 36. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model B2: } \Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$$

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 37. Conditional Mean and Conditional Volatility Models for Mallorca

Model B2: $\Delta_7 y_t = \phi_0 + \phi_1 \Delta_7 y_{t-1} + \varepsilon_t$

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.

Model B3

Tables 36-39 give the conditional means and conditional volatilities of the daily passenger arrivals to the Balearic Islands, Ibiza, Menorca and Mallorca, respectively, for Model B3. 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.

Table 38. Conditional Mean and Conditional Volatility Models for the Balearic Islands

$$\text{Model B3: } y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	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 39. Conditional Mean and Conditional Volatility Models for Ibiza

Model B3: $y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	30.12*	25.986*	-7.852*
	(48.54)	(52.119)	(53.585)
ϕ_1	0.049	0.047	0.053
	(0.011)	(0.011)	(0.011)
ϕ_2	0.967	0.967	0.949
	(0.011)	(0.010)	(0.012)
ϕ_3	0.176	0.178	0.177
	(0.023)	(0.024)	(0.023)
ϕ_4	0.808	0.814	0.834
	(0.024)	(0.026)	(0.028)
ω	5507.47	4820.05	0.101*
	(1696.98)	(1594.94)	(0.092)
GARCH/GJR α	0.612	0.723	--
	(0.097)	(0.145)	
GJR γ	--	-0.219*	--
		(0.115)	
GARCH/GJR β	0.609	0.614	--
	(0.028)	(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 40. Conditional Mean and Conditional Volatility Models for Menorca

Model B3: $y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} y_{t-1} + \phi_2 \delta_{\mathrm{H}} y_{t-7} + \phi_3 \delta_{\mathrm{L}} y_{t-1} + \phi_4 \delta_{\mathrm{L}} y_{t-1} + \varepsilon_t$

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 41. Conditional Mean and Conditional Volatility Models for Mallorca

Model B3: $y_t = \phi_0 + \phi_1 \delta_H y_{t-1} + \phi_2 \delta_H y_{t-7} + \phi_3 \delta_L y_{t-1} + \phi_4 \delta_L y_{t-1} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_0	-63.040*	-64.522*	119.71*
	(139.46)	(165.45)	(198.43)
ϕ_1	0.033	0.032	0.030
	(0.004)	(0.005)	(0.006)
ϕ_2	0.971	0.971	0.970
	(0.005)	(0.005)	(0.006)
ϕ_3	0.034	0.034	0.026
	(0.012)	(0.012)	(0.010)
ϕ_4	0.999	1.000	0.999
	(0.011)	(0.011)	(0.011)
ω	768923.6	738865.1	1.284
	(80740.1)	(80616.6)	(0.415)
GARCH/GJR α	0.428	0.455	--
	(0.026)	(0.033)	
GJR γ	--	-0.050*	--
		(0.042)	
GARCH/GJR β	0.587	0.590	--
	(0.014)	(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.

Model B4

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 B4 in Tables 40-43, 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 B1, B2 and B3 are not statistically significant in any of the four data sets. However, the asymmetry coefficient is positive and statistically significant in Model B4 for Ibiza and Menorca (see Tables 41 and 42, 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 42. Conditional Mean and Conditional Volatility Models for the Balearic Islands

Model B4: $\Delta_7 y_t = \phi_0 + \phi_1 \delta_H \Delta_7 y_{t-1} + \phi_2 \delta_L \Delta_7 y_{t-7} + \varepsilon_t$

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 43. Conditional Mean and Conditional Volatility Models for Ibiza

$$\text{Model B4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_H \Delta_7 y_{t-1} + \phi_2 \delta_L \Delta_7 y_{t-7} + \varepsilon_t$$

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 44. Conditional Mean and Conditional Volatility Models for Menorca

$$\text{Model B4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\mathrm{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\mathrm{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	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 45. Conditional Mean and Conditional Volatility Models for Mallorca

$$\text{Model B4: } \Delta_7 y_t = \phi_0 + \phi_1 \delta_{\text{H}} \Delta_7 y_{t-1} + \phi_2 \delta_{\text{L}} \Delta_7 y_{t-7} + \varepsilon_t$$

Parameters	GARCH	GJR	EGARCH
ϕ_0	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.

Likelihood ratio test

Table 44 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.

Table 46. 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.

5.6 Conclusion

This Chapter has tested the existence of a zero frequency unit root for the arrivals and for the weekly differences for the Balearic Islands as well as for Palma, Ibiza and Mahon. It has specified the two models used to estimate passenger arrivals and the weekly differences in passenger arrivals, and has also tested the significance of distinguishing between the high and low seasons in terms of explaining daily and weekly passenger arrivals. as well as their respective volatilities.

Finally it has provided an interpretation of the empirical results of the estimates for the conditional mean which are estimated simultaneously with the estimates of the corresponding conditional volatility models, that is, using GARCH(1,1), GJR(1,1) and EGARCH(1,1). 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.

Chapter 6. CONCLUSION

This research is devoted to the modelling of international tourism arrivals to the main tourist regions in Spain. As it is well known, during the last decades tourism is among the most successful economic activities, with a significant contribution in income and employment generation worldwide. As an exporting sector international tourism generates significant receipts which are crucial for many countries. In the particular case of Spain, the country is the second world leader in terms of total international tourist arrivals and international tourism receipts. As in any non-storable-good producing industry, the accurate forecast and understanding of demand is critical for the accurate management of the activity. Although tourism demand has been extensively researched in the previous literature, this research has presented a different approach to tourism demand by modelling the behavior of the conditional variance.

Some modern financial econometric time series techniques that were developed to understand and model volatility, otherwise known as risk in finance, were applied to analyze international tourist arrivals in different regions within Spain. The main reason for applying these financial econometric techniques to the analysis of tourism demand is that the existence of time-varying variances has important implications for the construction of confidence intervals of forecasts, and for the risk associated with tourism demand in different regions. In an international context in which natural disasters, terrorism, crime and ethnic conflicts, among others, have significant impacts on tourism, it is crucial to assess the persistence of shocks on tourist arrivals for effective crisis management plans.

This research applies the conditional variance modeling to two sets of data with a distinct time and geographical aggregation pattern. The first dataset includes monthly international tourist arrivals to the five main tourist regions in Spain and the aggregate from January 1997 to April 2007, giving a total of 126 observations. These regions accounted for more than 84% of total international tourist arrivals to Spain in 2006. Chapter 3, analyzes and compares the characteristics of the tourism activity in the main tourist regions in Spain. The distinct economic impact of tourism in those regions is also presented.

The second database has a narrower geographical distribution including only one of the above regions, namely the Balearic Islands. Of the five major tourist regions in Spain, these groups of Islands are one of the most popular destinations with a highly tourism specialized economic pattern. This second data set differs form the previous one in the sense that it provides daily frequency and uses air passenger arrivals. This temporal disaggregation is particularly useful for the analysis of volatility that is proposed in this research. Hence, the dataset includes 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). The analyzed period goes from 1 January 2001 to 31 December 2006 adding a total of 2,191 observations. The source of data was the AENA (Aeropuertos Españoles y Navegación Aérea), the Spanish National Airport Authority.

Univariate time series models are estimated for the conditional means of tourist arrivals, as well as their conditional volatilities. The estimated conditional volatility models were GARCH(1,1), GJR(1,1) and EGARCH(1,1). Both the second moment and log-moment conditions were calculated to provide diagnostic checks of the estimated models. The stationarity of the time series data was tested using modified unit root tests. The conditional mean estimates were generally statistically adequate, and the conditional volatility estimates were found to be meaningful, as well as consistent and asymptotically normal, so that inferences were valid.

The study 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 research also defines three other types of asymmetric behaviour, namely low season financial risk, overcrowding through overbooking and congestion, and tourism saturation.

The results obtained from modelling monthly international tourist arrivals to Spain and the five main tourist regions, and their associated volatility are presented in Chapter 4. The hypothesis regarding the presence of unit root is not strongly rejected for the variable in levels, while yearly changes are found to be stationary in all six data sets under analysis. GARCH(1,1), GJR(1,1) and EGARCH(1,1) conditional volatility models are applied to the level and yearly change of monthly tourist arrivals to Spain and its five main tourist regions. The conditional mean estimates were generally statistically adequate, and the conditional volatility estimates were found to be meaningful, as well as consistent and asymptotically normal, so that inferences were valid. The results presented in the chapter prove the differences in the parameters obtained from the aggregate sample of tourism arrivals to Spain as compared with the estimates for each of the five main tourist Regions. The ultimate objective is to obtain precise information regarding the degree of regional diversification of the tourism industry, which may help to reduce the economic and financial risks for the country as a whole.

For the daily frequency database, passenger arrivals, was found to be stationary for each of the three islands, as well as for the Balearics. Level and weekly difference of passenger arrivals were used to model the conditional, 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 this research 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. These modern financial econometric time series techniques models can also be applied to daily cruise passenger arrivals. It must be emphasized that the main reason for applying these financial econometric techniques is because it has important implications for the construction of confidence intervals of estimates and of forecasts, it is also essential to study the risk (or uncertainty) associated with tourism demand, and consequently it is relevant for the design of efficient tourism policies.

REFERENCES

AEA (2005), *Informe Anual del Turismo en Andalucía 2005,* Sevilla, Analistas Económicos Andalucía.

Aguiló, E., Alegre, J., & Riera, A. (2001). Determinants of the price of German tourist packages on the island of Mallorca. *Tourism Economics, 7*(1), 59-74.

Aguiló, E., Riera, A., & Rosselló, J. (2005). The short-term price effect of a tourist tax through a dynamic demand model: The case of the Balearic Islands. *Tourism Management, 26*(3), 359-365.

Alegre, J. and M. Cladera (2006), Repeat Visitation in Mature Sun and Sand Holiday Destinations, *Journal of Travel Research,* 44(3), 288-297.

Alegre, J., & Pou, L. (2006). The length of stay in the demand for tourism. *Tourism Management, 27*, 1343-1355..

Bollerslev, T. (1986), Generalised autoregressive conditional heteroscedasticity, *Journal of Econometrics*, 31, 307-327.

Bonn, I., and Rundle-Thiele, S. (2007). Do or die-Strategic decision-making following a shock event. *Tourism Management*, 28: 615-620.

Boussama, F. (2000), Asymptotic normality for the quasi-maximum likelihood estimator of a GARCH model, *Comptes Rendus de l'Academie des Sciences,* Serie I (131), 81-84 (in French).

Buhalis, D. (2001), The tourism phenomenon: the new tourist and consumer, in S. Wahab and C. Cooper (eds.), *Tourism in the Age of Globalization,* London, Routledge, pp. 69-96.

Bujosa, A., & Rossello, J. (2007). Modelling environmental attitudes towards tourism. *Tourism Management, 28*, 688-695.

CAIB. (2004). *Input/Output. Marco de las Islas Baleares 2004.* Palma de Mallorca: Govern de les Illes Balears.

Capó, J., Riera, A., & Rosselló, J. (2007) Accommodation determinants of seasonal patterns. *Annals of tourism reserach*, 34 (2), 422-436.

Chan, F., Lim, C., & McAleer, M. (2005). Modelling multivariate international tourism demand and volatility. *Tourism Management, 26*, 459-471.

Chan, Y.-M., T.-K. Hui and E. Yuen (1999), Modeling the impact of sudden environmental changes on visitor arrival forecasts: the case of the Gulf war, *Journal of Travel Research,* 37, 391-394.

CITTIB (2007), *El turisme a les Illes Balears. Dades informatives 2006*, Palma de Mallorca, Spain, Centre d'Investigació i de Tecnologies Turístiques.

CRE. (2005). *Informe econòmic i social de les Illes Balears*. Palma de Mallorca: Centre de Recerca Econòmica.

Crouch, G.I. (1994), The Study of International Tourism Demand: A Review of Findings, *Journal of Travel Research,* 33, 12-23.

Crouch, G.I. (1995), A Meta-Analysis of Tourism Demand, *Annals of Tourism Research,* 22, 103-118.

Daniels, M.J. and W.C. Norman (2003), Estimating the Economic Impacts of Seven Regular Sport Tourism Events, *Journal of Sport Tourism,* 8(4), 214-222.

Daniels, M.J., W.C. Norman and M.S. Henry (2004), Estimating Income Effects of A Sport Tourism Event, *Annals of Tourism Research,* 31(1), 180-199.

Dickey, D.A. and W.A. Fuller (1979), Distribution of the estimators for autoregressive time series with a unit root, *Journal of American Statistical Association,* 74, 427-431.

Dickey, D.A. and W.A. Fuller (1981), Likelihood ratio statistics for autoregressive time series with a unit root, *Econometrica,* 49, 1057-1072.

Dirección General Turismo (2006), *Datos Estadísticos 2006,* Madrid, Comunidad de Madrid.

Elie, L. and T. Jeantheau (1995), Consistency in heteroskedastic models, *Comptes Rendus de l'Académie des Sciences,* Série I, 320, Série I, 320, 1255-1258 (in French).

Elliot, G., T.J. Rothenberg and J.H. Stock (1996), Efficient tests for an autoregressive unit root, *Econometrica,* 64, 813-836.

Engle, R.F. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica,* 50, 987-1007.

Eugenio-Martin, J., Sinclair, M. T., and Yeoman, I. (2005). Quantifying the effects of tourism crises: An application to Scotland. *Journal of Travel & Tourism Marketing*, 19 (21-34).

Exceltur (2007), *Impactur 2006,* Palma de Mallorca, Govern de les Illes Balears..

Faulkner, B. and R. Russell (2000), Turbulence, chaos and complexity in tourism systems: A research direction for the new Millenium In B. Faulkner, G. Moscardo and E. Laws (Eds.), *Tourism in the 21st century, reflections on experience* (pp. 328-349). London: Continuum.

Faulkner, B. and R. Russell (2002), Chaos and Complexity in Tourism: In search of a New Perspective. In B. Faulkner (Ed.), *Progressing tourism research.* Sydney: Channel View Publications.

Floyd, M.F., H. Gibson, L. Pennington-Gray and B. Thapa (2003), The Effects of Risk Perceptions on Intentions to Travel in the Aftermath of September 11, 2001, *Journal of Travel & Tourism Marketing,* 15(2/3), 19-38.

Francis, G., I. Humphreys and S. Ison (2004), Airports' perspectives on the growth of low-cost airlines and the remodeling of the airport-airline relationship, *Tourism Management,* 25(4), 507-514.

Garin, T., and Montero, L.F. (2007). Tourism in the Balearic Islands: A dynamic model for international demand using panel data. *Tourism Management, 28*(5), 1224-1235.

Gelan, A. (2003), Local economic impacts: The British Open, *Annals of Tourism Research,* 30(2), 406-425.

Glosten, L., R. Jagannathan and D. Runkle (1992), On the relation between the expected value and volatility of nominal excess return on stocks, *Journal of Finance,* 46, 1779-1801.

Hodur, N.M., D.A. Bangsund, F.L. Leistritz and J. Kaatz (2006), Estimating the contribution of a multipurpose event facility to the area economy, *Tourism Economics,* 12(2), 303-316.

Hoti, S., M. McAleer and R. Shareef (2007), Modelling international tourism and country risk spillovers for Cyprus and Malta, *Tourism Management,* 28, 1472-1484.

Huang, J. H., and Min, J. C. (2002). Earthquake devastation and recovery in tourism: The Taiwan case. *Tourism Management*, 23 (145-154).

IET (2006a), *Encuesta de Gasto Turístico (EGATUR)*, Madrid, Instituto de Estudios Turísticos.

IET (2006b), *Movimientos Turísticos en Fronteras (FRONTUR)*, Madrid, Instituto de Estudios Turisticos.

IET (2007), *Balance del Turismo en España en 2006*, Madrid, Instituto de Estudios Turísticos.

INE. (2007). Demografía y Población. [Electronic Version]. Retrieved 16/July/2007 from http://www.ine.es/inebase/cgi/axi.

Ivars, J.A.(2004), Tourism Planning in Spain. Evaluation and perspectives, *Annals of Tourism Research,* 31(2), 313-333.

Jeantheau, T. (1998), Strong consistency of estimators for multivariate ARCH models, *Econometric Theory,* 14, 70-86.

Kim, S.S. and K.K.F. Wong (2006), Effects of News Shock on Inbound Tourist Demand Volatility in Korea, *Journal of Travel Research,* 44(4), 457-466.

Knowles, T., & Curtis, S. (1999). The market viability of European mass tourist destinations. A post-stagnation life-cycle analysis. *International Journal of Tourism Research, 1*(2), 87-96.

Kozak, M. (2001a), Comparative assessment of tourist satisfaction with destinations across two nationalities, *Tourism Management,* 22, 391-401.

Kozak, M. (2001b), Repeaters' behavior at two distinct destinations, *Annals of Tourism Research,* 28(3), 784-807.

Kozak, M. (2002), Destination Benchmarking, *Annals of Tourism Research,* 29(2), 497-519.

Law, R. (2001). The impact of the Asian financial crisis on Japanese demand for travel to Hong Kong: A study of various forecasting techniques. *Journal of Travel & Tourism Marketing,* 10: 47-66.

Lee, S.W. and B.E. Hansen (1994), Asymptotic theory for the GARCH(1,1) quasi-maximum likelihood estimator, *Econometric Theory,* 10, 29-52.

Li, W.K., S. Ling and M. McAleer (2002), Recent theoretical results for time series models with GARCH errors, *Journal of Economic Surveys,* 16, 245-269. Reprinted in M. McAleer and L. Oxley (eds.), *Contributions to Financial Econometrics: Theoretical and Practical Issues*, Blackwell, Oxford, 2002, pp. 2009-2033.

Li, G., H. Song and S.F. Witt (2005), Recent Developments in Econometric Modeling and Forecasting, *Journal of Travel Research,* 44(1), 82-99.

Lim, C. (1997a), An Econometric Classification and Review of International Tourism Demand Models, *Tourism Economics,* 3, 69-81.

Lim, C. (1997b), Review of International Tourism Demand Models *Annals of Tourism Research,* 24, 835-849.

Lim, C. (1999), A Meta-Analytic Review of International Tourism Demand, *Journal of Travel Research,* 37, 273-284.

Ling, S. and M. McAleer (2002a), Necessary and sufficient moment conditions for the GARCH(r,s) and asymmetric power GARCH(r,s) models, *Econometric Theory,* 18, 722-729.

Ling, S. and M. McAleer (2002b), Stationarity and the existence of moments of a family of GARCH processes, *Journal of Econometrics,* 106, 109-117.

Ling, S. and M. McAleer (2003a), Asymptotic theory for a vector ARMA-GARCH model, *Econometric Theory,* 19, 278-308.

Ling, S. and M. McAleer (2003b), On adaptive estimation in nonstationary ARMA models with GARCH errors, *Annals of Statistics,* 31, 642-674.

Ling, S. and W.K. Li (1997), On fractionally integrated autoregressive moving-average models with conditional heteroskedasticity, *Journal of the American Statistical Association,* 92, 1184-1194. .

Lundtorp, S. (2001), Measuring Tourism Seasonality. In T. Baum and S. Lundtorp (Eds.), *Seasonality in Tourism* (pp. 23-50). Oxford: Elsevier

McAleer, M. (2005), Automated inference and learning in modeling financial volatility, *Econometric Theory,* 21, 232-261.

McAleer, M., F. Chan and D. Marinova (2007), An econometric analysis of asymmetric volatility: theory and application to patents, *Journal of Econometrics,* 139, 259-284.

Nelson, D.B. (1991), Conditional heteroscedasticity in asset returns: a new approach, *Econometrica,* 59, 347-370.

Ng, S. and P. Perron (2001), Lag length selection and the construction of unit root tests with good size and power, *Econometrica,* 69, 1519-1554.

Perron, P. and S. Ng (1996), Useful modifications to some unit root tests with dependent errors and their local asymptotic properties, *Review of Economic Studies,* 63, 435-463.

Phillips, P.C.B. and P. Perron (1988), Testing for a unit root in time series regression, *Biometrika,* 75, 335-346.

Poon, A. (1993), *Tourism, Technology and Competitive Strategies*, Oxford, CAB International.

Prideaux, B., B. Laws and B. Faulkner (2003), Events in Indonesia: exploring the limits to formal tourism trends forecasting methods in complex crisis situations, *Tourism Management,* 24, 475-487.

Rosselló, J., Aguiló, E., and Riera, A. (2005) Modeling Tourism Demand Dynamics. *Journal of Travel Research*, 44 (1): 111-116.

Rosselló, J., Riera, A., & Sansó, A. (2004). The economic determinants of seasonal patterns. *Annals of tourism reserach*, 31 (3), 697-711.

Russell, R. and B. Faulkner (1999), Movers and shakers: chaos makers in tourism development, *Tourism Management,* 20(4), 411-423.

Santana, G. (2003), Crisis Management and Tourism: Beyond the Rhetoric, *Journal of Travel and Tourism Marketing,* 15(4), 299-321.

Shareef, R., & McAleer, M. (2007). Modelling the uncertainty in monthly international tourist arrivals to the Maldives. *Tourism Management, 28*(1), 23-45.

Shephard, N. (1996). Statistical aspects of ARCH and stochastic volatility. In O.E. Barndorff-Nielsen, D.R. Cox & D.V. Hinkley (eds.), *Statistical Models in Econometrics, Finance and Other Fields* (pp. 1-67). London: Chapman & Hall.

Sinclair, T. and M. Stabler (1997), *The Economics of Tourism*, London. Routledge.

Sinclair, T. and S. Page (1993), The Euroregion. A new framework for tourism and regional development, *Regional Studies*, 27, 475-483.

Skalpe, O. (2003), Hotels and restaurants--are the risks rewarded? Evidence from Norway, *Tourism Management,* 24(6), 623-634.

Smith, E.L.J. (1998), Tourism as an industry: debates and concepts, in D. Ioannides and K. Debbage (eds). *The Economic Geography of the Tourist Industry*, Routledge, pp. 31-52.

Song, H. and G. Li (2008), Tourism demand modelling and forecasting-A review of recent research, *Tourism Management,* 29, 203-220.

Sönmez, S. (1998), Tourism, terrorism, and political instability, *Annals of Tourism Research,* 25, 416-456.

Tisdell, C. (2000), *The Economics of Tourism,* The International Library of Critical Writtings in Economics, Elgar Reference collection, Cheltenham, UK and Northampton, MA, USA

Tsitouras, A. (2004), Adjusted Gini coefficient and “months equivalent” degree of touristm seasonality: a research note, *Tourism Economics*, 10(1), 95-100

UNWTO (2007), Start to 2007 exceeds forecasts, *World Tourism Barometer,* 5(2).

Vanhove, N. (2001), Globalisation of tourism demand, global distribution systems and marketing. In S. Wahab and C. Cooper (Eds.), *Tourism in the Age of Globalisation* (pp. 123-156). London: Routledge.

Williams, G. (2001), Will Europe's charter carriers be replaced by "no frills" scheduled airlines?, *Journal of Air Transport Management,* 7(5), 277-286.

Witt, S.F. and C.A. Witt (1995), Forecasting Tourism Demand: A Review of Empirical Research, *International Journal of Forecasting,* 11, 447-475.