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Cruising is Risky Business

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Abstract

As the fastest growing sector within the international tourism industry, having grown at roughly double the rate of international tourism as a whole, the cruise liner business has shown impressive growth in the North American and European markets. For port management purposes, as well as for transport policy, it is essential to be able to forecast accurately cruise passenger arrivals and their variability. In the presence of time-varying variances (or volatility), it is crucial to model such volatility in order to provide sensible forecast intervals in addition to the forecast themselves. Time-varying volatility in port management is important because governments and businesses need to be aware of the uncertainty associated with the number of cruise passenger arrivals and their associated growth. In calculating income elasticities, port taxes and tourist taxes, it is essential to obtain accurate estimates of cruise passenger arrivals and their volatility. Moreover, 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 cruise passenger arrivals for effective crisis management plans, including different forms of co-operation among ports facing similar shocks. Appropriate models are required to enable optimal private and public decision making in designing ports for cruise ships. Daily cruise passenger arrivals data for the three major ports in the Balearic Islands, Spain, namely Palma, Ibiza and Mahon, for the period 1997-2006, as well as for the high cruise season for each island,are analyzed using alternative conditional mean and conditional volatility models in order to provide empirical support for purposes of optimal decision making. Four different types of asymmetries are analyzed according to the positive and negative shocks to daily cruise passenger arrivals, as well as from distinctions between the high and low cruise seasons. The estimates of cruise passenger arrivals and their volatility are generally found to be sensible and to have valid statistical properties. Likelihood ratio tests of the constancy of coefficients in the high and low cruise seasons indicate that the weekly delayed response of cruise passenger arrivals differ significantly spatially across islands and temporally across seasons.

Keywords: Asymmetric responses to shocks**,** Conditional volatility models, Cruise passenger arrivals, Efficient port management, High and low tourist seasons, International tourism

1. Introduction

The cruise liner business is considered to be the fastest growing sector within the international tourism industry. In recent decades, it has grown at roughly double the rate of international tourism as a whole (Wood, 2004). While the North American market leads the cruise industry, the most impressive growth has occurred in Europe, with leading US and European based cruise lines expanding prominently in the Mediterranean (UNWTO, 2007).

For port management purposes, as well as for transport policy (Leigh, L. and Thampapillai, 1998), it is essential to be able to forecast cruise passenger arrivals and their percentage changes accurately. As it is important to provide sensible 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 and cruise passenger 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 cruise passenger arrivals and their respective rates of growth. In this sense, models of cruise passenger arrivals and their associated time-varying volatilities can make a significant contribution to port risk management policy.

There are several arguments investigating and modelling time-varying volatility in port management. First, governments and businesses need to be aware of the uncertainty associated with the number of cruise passenger arrivals and their associated growth, as they are increasingly involved in the planning, development, management and marketing of ports (Helling and Poister, 2000). For purposes of calculating the income elasticity of demand, port taxes or other kinds of tourist taxes, it is necessary to consider accurate estimates of cruise passenger arrivals and their volatility. Second, in an international context in which unpredictable events, such as natural disasters, terrorism, crime and ethnic conflicts, have significant impacts on tourism, it will become increasingly important to assess the persistence of positive and negative shocks on cruise passenger arrivals to design effective crisis management plans. This allows for different forms of co-operation among ports that face similar shocks. Third, these temporal series models also admit different levels of time and spatial aggregation that may shed light on the optimal design of infrastructure for ports and for planning the necessary services, and for considering the optimal level of centralized planning and/or privatization (Gross, 1998).

Almost 70% of the demand for international cruisers originates in North America (Wood, 2000). Figures from the Cruise Lines International Association (CLIA) members, which account for 97% of North American passengers, showed that, in 2005, over 9.6 million North Americans embarked on a cruise, and is forecasted to grow at an annual rate of 8% (CLIA, 2006). The second most important generating market is the UK, with over 1 million cruise passengers in 2005, Germany is third with 600,000 passengers, and is predicted to reach 1 million cruise passengers by 2010 (PSA, 2006). In Asia, Japan is the most important generating market, with nearly 200,000, passengers yearly (Wild, 2006).

The average age of a North American cruise passenger is 49 years (CLIA, 2006). For the British market it is 53.5, but decreasing yearly, whereas in the early 1990s this figure was around 60 years (PSA, 2006). For this reason, cruise passengers are more likely to have retired (CLIA, 2006). As the average age of a typical cruise passenger falls, the number of potential cruise passengers in the income and age profiles is rising (Smeeding and Sullivan, 1998; Deaton and Paxson, 1998). Consequently, the number of potential cruise passengers is rising. Another aspect that makes the cruise industry unique in comparison with other tourism-related sectors is its high occupancy rate which, at an annual average of over 90%, is very high compared with typical hotel and resort occupancy rates (Wild, 2006).

The plan of the remainder of the paper is as follows. Section 2 discusses cruise ship destinations in the Caribbean, Alaska, Asia-Pacific, Northern Europe and the Mediterranean. The data are discussed in Section 3. Conditional mean and conditional volatility models are presented in Section 4 to provide empirical support for purposes of optimal decision making. The estimation results are presented in Section 5, and some concluding remarks are given in Section 6.

2. Cruise Ship Destinations

Destinations are a main feature in the cruise experience. The cruise product is a combination of the ship and the destinations it visits. A destination is a mixture of attractions and services, where each part is dependent upon others for success in attracting, servicing and satisfying the tourist (Mill and Morrison, 1992). According to Klein (2006, p. 266), "many ports have a love-hate relationship with the cruise industry." On the one hand, ports do not want to be omitted from cruise itineraries, but on the other, they feel they are not receiving a fair share of the cruise tourist expenditure. In fact, cruise ships are becoming larger, increasing the number of activities and entertainment on board so that, in many cases, ports of call have become almost secondary (Dowling, 2006). However, there are many new terminals being built and old ones being upgraded around the world (Wild, 2006). In other words, many destinations are willing to invest in infrastructure to attract cruise visitors, and hence generate foreign revenue, although some destinations, in particular small islands (as in the case of Bermuda), are having to limit the number of cruise arrivals to maintain the quality of life for residents and to reduce overcrowding (Teye, 2006).

Few papers have discussed the economics of cruise tourism. From the industry perspective, Papatheodorou (2006) uses industrial economics to analyze the oligopolistic position of the three main world cruise companies, while Wie (2005) applies the Stackelberg equilibrium strategy to find the optimum equilibrium capacity and investment decisions based on this dynamic oligopolistic competition. Others have mentioned that, generally, ships are bigger than ever, thereby creating a mass customized product and allowing companies to achieve economies of scale (Klein, 2006; Weaver, 2005).

From the geographic perspective of cruising, among others, Dwyer and Forsyth (1998) examine the different economic impacts generated by cruise tourism at the regional and national levels for policy purposes using Australian data. Mescon and Vozikis (1985), and Braun and Tramell (2006) use an input-output model to measure the direct economic impact generated by cruise tourism in Miami and in Port Canaveral, respectively. Pratt and Blake (2007) use a computable general equilibrium model to estimate the economy-wide economic impact of the cruise industry to Hawaii. Finally, Klein (2006) examines, from a more general perspective, the interactions between ports and cruise companies, through ownership of cruise terminals and the power of cruise lines to negotiate passenger fees.

Some ports act as a home port because they have a strategic position, a major airport, suitable accommodation facilities, or other services for cruisers to embark and/or disembark. Other ports, some of which are also home ports, are included in cruise itineraries, acting as ports of call, and hosting cruisers in the majority of cases, as day visitors.

There are five major cruise passenger destination regions, namely the Caribbean and Alaska in the American Continent, the Asia-Pacific region, and the two differentiated European regions of Northern Europe and the Mediterranean (Butler, 2003).

The Caribbean

The most important destination with respect to the number of cruise passenger visitors is, without a doubt, the Caribbean (Cartwright and Baird, 1999). In 2005, the top nine world cruise ports belonged to the Caribbean area. As this area enjoys a warm and sunny climate during the Northern Hemisphere's winter, more than one-half of the total cruise passenger capacity visits the Caribbean between October and April (Wild, 2006). Although the cruise business in the Caribbean is forecasted to continue growing, the growth rates will decrease (Wilkinson, 2006).

There are over 7,000 islands in the Caribbean, and its proximity to Florida makes it a perfect destination for intensive port itineraries (Hall and Braithwaite, 1990). Cruise passengers in the Caribbean can visit many countries, with very different cultural backgrounds, in a seven-day cruise (Ward, 2005). There are three main sub-areas, namely Eastern, Western and Southern Caribbean (see Table 1).

Table 1: The Caribbean

Western	Eastern	Southern
Jamaica	American Virgin Islands	Mexico
Cayman Islands	British Virgin Islands	Belize
Turks and Caicos Islands	Saint Martin	Honduras
Cuba	Dominica	Nicaragua
Haiti	Barbados	Costa Rica
Florida	Saint Lucia	Panama
Dominican Republic	Martinique	Colombia
Puerto Rico	Guadalupe	Venezuela
	Saint Vincent and the Grenadines	Aruba
	Saint Kitts and Nevis	Curaçao
	Antigua and Barbuda	Bonaire
	Granada	Trinidad and Tobago
	Anguila	
	Monserrat	
	Saba	
	Saint Eustatius	

Source: Butler (2003)

The Eastern Caribbean was the first area to be developed for cruising due to its proximity to Miami (Cartwright and Baird, 1999), and the first to offer seven-day itineraries (Butler, 2003). Miami is the most important base port, not only in the Caribbean, but worldwide, with an estimated 1,380,750 cruise passengers disembarking yearly (Wild, 2006). A total of 3.6 million passengers used the port in 2005 (Miami, 2007). In fact, Miami can handle up to 8,400 passengers per hour in the embark/disembark operation (Butler, 2003).

The Panama Canal can also be included in the Caribbean area. Trans-canal cruises typically depart from Fort Lauderdale (Ward, 2005), also known as the Everglades, and is ranked second worldwide in terms of the number of cruise passengers (Wild, 2006). The Panama Canal is also important for moving ships to be in the correct location according to the season (Cartwright and Baird, 1999), otherwise known as deployment. However, many of the new vessels are too large for the Panama Canal. These post-Panamax cruise ships cannot be deployed to Alaska from the Caribbean during the Northern Hemisphere summer months (Charlier and McCalla, 2006).

Alaska

Alaska is a specialized region, where on-land excursions are extremely important in the tourism decision process (Butler, 2003), and 80% of its main market originates from North America (Munro and Gill, 2006). These excursions include floatplane, helicopter and train tours (Ward, 2005) Although Alaska is visited only during a few months in the year, the cruise industry represents about 8% of the total cruise industry in the USA (Munro and Gill, 2006). There is great concern among environmentalists that saturation levels have been reached in this region. In fact, most of the literature published on cruise tourism within this region has focused on the environmental and sustainability dimension of tourism.

Asia-Pacific

The Asia-Pacific region is divided into four sectors, as given in Table 2:

Table 2: Asia-Pacific

South Pacific	Southeast Asia	Far East	Trans-Pacific
Australia	Malaysia	Japan	Hawaii
New Zealand	The Philippines	Republic of Korea	Fiji
Solomon Islands	Singapore	D.P.R. Korea	French Polynesia
Indonesia	Vietnam	China	
Papua Asia	Cambodia		
Papua New Guinea	Thailand		

Source: Butler (2003).

Cruise lines have developed new itineraries to meet the demands of the repeat cruise passengers, and Australia offers a safe and attractive destination, especially for US cruisers (Miller and Grazer, 2002). Nevertheless, Star cruises, based in Singapore, target the Asian market, which has a great growth potential. Furthermore, Sydney, Auckland, Singapore and Hong Kong, all cities with great traditions as logistic ports, are investing heavily in new facilities for cruise passengers (Butler, 2003), as well as the port of Shangai and the port of Tianjin, used as a gateway to Beijing (Ledger, 2007).

Hawaii is also a standout in the cruise map, with three ports among the 20 leading cruise destinations in the North American coastline (Wild, 2006). Cruise passenger numbers have grown at an average annual growth rate of 16.5% between 1996 and 2005 (Pratt and Blake, 2007).

Northern Europe

The Baltic Sea and Atlantic Europe have similar natural attractions as Alaska, but the main attraction of this area lies in the cultural diversity of its ten countries. This area covers Russia, the Norwegian Fjords, the British Isles and Iceland. The main source market is European and suffers very high seasonality, with practically no business during the cold months (Butler, 2003).

The Mediterranean

Among all the different cruise areas, the Mediterranean has experienced the most spectacular growth. As an example, between 1987 and 1999 overnight stays increased by 700%. Butler (2003) gives the following reasons for this growth: the growth of UK passengers, new genuine European cruise lines, an increase in the worldwide supply of cruise ships, and commercial agreements between British tour-operators and big US cruise companies.

As for the Caribbean, the Mediterranean enjoys mild climatic conditions and cultural diversity, in history, gastronomy, religion, architecture and tradition, which makes it a very appealing cruise area. Furthermore, the growth potential in EU source markets is extremely high, including Mediterranean countries themselves, such as Spain and France (PSA, 2003). However, it is expected that non-Europeans cruising the Mediterranean will grow at a faster rate than European markets (UNWTO, 2007).

The Mediterranean is divided into three main areas, namely Western, Eastern and the Adriatic. The leading cruise ports are classified in Table 3. These are presented vertically by cruising area and horizontally by the number of cruise passengers. The Mediterranean has the European leading destination ports in the number of cruisers, with

Barcelona in first place and 11th worldwide. Venice, in the Adriatic, is number 2 in Europe and 16th worldwide. Both Citavecchia (Rome) and Palma de Mallorca are the next leading destinations in Europe, and both reached the Top 20 worldwide in 2005 (Wild, 2006).

Table 3: The Mediterranean

Western	Eastern	Adriatic
Barcelona	Piraeus	Venice
Citavecchia	Santorini	Dubrovnik
Palma de Mallorca	Limasol	Katakolon
Naples	Mykonos	Corfu
Savona	Rhodes	Bari
Livorno	Kusadasi	
Tunis/ La Goulette	Istanbul	
Valetta	Heraklion/Crete	
Genoa		
Marseille		
Nice-Villefranche		
Malaga		
Palermo		
Messina		
Gibraltar		
Monte Carlo		

Source: Wild (2006)

Within the European embarkation ports, Spain was ranked second, with Barcelona and Palma de Mallorca as the major port cities (Wild, 2007). In 2005, the port of Palma was ranked number 19 in the world in the number of cruise passengers embarking and disembarking and, as stated earlier, occupies fourth position within Mediterranean ports.

Another aspect which must be highlighted is that the cruise industry is “governed by seasonality and repositioning” (Charlier and McCalla, 2006, p. 27). While most destinations are affected by weather seasons, cruise ships may be moved from one side of the world to the other. This repositioning, or deployment, of ships makes cruises a year-round proposition. On the other hand, as Wood (2006, p. 404) states, “the cruise industry is deeply rooted in - and dependent upon – key globalization processes and projects.”

Table 4 gives the percentage of cruise beds located around the globe during the four seasons in 2004.

Table 4: Deployment of International Cruise Capacity 2004 (%)

Season / Region	Dec-Jan-Feb	Mar-Apr-May	Jun-Jul-Aug	Sep-Oct-Nov
Caribbean	57.6	48.4	23.8	53.1
Mediterranean	4.9	28.6	30.3	26.4
North Europe	0.3	18.7	18.8	4.3
Alaska	0	17.8	15.3	0

Source: Wild (2006)

In short, the forecast for the cruise industry is very optimistic. Based on the number of ships being ordered, the increasing size of the new ships, and the continuous deployment of North American ships to Europe, it is predicted that by 2010 European ports could have nearly 20.6 million cruise passenger visits (Wild, 2007). Additionally, the new ships being commissioned are able to sail in rough seas, so that the cruise season is likely to expand. Furthermore, itinerary planners are increasingly searching for new destinations to satisfy their customers. It is also predicted that ships will stay longer at ports which have more to offer, so that the economic impact on the destination will be greater (Barron and Bartolomé, 2006).

Ports in the Balearics

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 2006 the Balearic Islands received, by air and sea, over 12.5 million tourists. 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).

Figure 1: The Main Mediterranean Cruise Ports

Source: www.islandcruises.com

The three main islands in the Balearics are Mallorca, Ibiza and Menorca, and all have cruise ship terminals in their respective capital cities of Palma de Mallorca, Ibiza and Mahon. The island of Formentera, opposite Ibiza, and the Port of Alcudia on the north of Mallorca, can also accommodate cruise ships, but the numbers are very small and erratic, and hence will not be analyzed in this paper.

In the Balearics, Palma is the most important port home port, as well as a port of call, and can handle up to seven cruise ships (CITTIB, 2005). Palma has grown at a spectacular average annual rate of around 16%, which is double the world cruising sector rate, and four times the average world growth rate of international tourist arrivals (see Figure 2).

In contrast, Ibiza and Mahon are much smaller and have shallow draughts. Furthermore, while Ibiza is very open to the sea, and hence is not protected, the opposite holds for Mahon, which is closed and narrow. As given in Figure 2, the yearly cruise passenger arrivals to Ibiza and Mahon have been relatively constant.

3. Data

The data were made available by the port authorities from the Balearic Islands (Autoritat Portuària de Balears). Data was then prepared for analysis. Data include cruises that used the port as a port of call, so that passengers who disembarked and embarked on the same day were counted only once. The data also include those ships which used the port as their base port, so that passengers who embarked to start their cruise were counted and, upon returning, typically after seven days, were counted again as disembarking passengers. It was, therefore, decided to include only tourist arrivals, as in the case with air passengers, that is, only disembarking cruise passengers, to avoid double counting.

Tables 5 and 6 give the descriptive statistics of daily cruise passenger arrivals for 1997-2006, with 3,652 observations for all three islands, and during the cruise season, with 1,840 observations for Palma and 1,220 observations for Ibiza and Mahon, respectively. For purposes of empirical analysis conducted in this paper, the cruise seasons are defined as May to October each year for Palma, and June to September for Ibiza and Mahon. As would be expected, the minimum daily cruise passenger arrivals are zero for all three islands during the year, as well as during the respective cruise seasons. In fact, the median daily cruise passenger arrivals are zero for both, Ibiza and Mahon during the year and during the high season.

The mean daily cruise passenger arrivals are higher in the cruise season for all three islands than during the year. The median is higher for Palma in the high season than during the year, and the maximum daily cruise passenger arrivals are higher in the cruise season for both Palma and Ibiza. Somewhat surprisingly, the maximum for Mahon for the period 1997-2006 occurs outside the cruise season. From Tables 5 and 6, it is clear that the distributions of daily cruise passenger arrivals are not normal, and are positively skewed for all three islands during the year as well as during the respective cruise seasons.

Graphs of daily cruise passenger arrivals, and their associated volatilities, to the three islands for 1997-2006 are given in Figures 3-5, while the corresponding graphs during the respective cruise seasons are given in Figures 6-8. There are significant differences in daily cruise passenger arrivals, as well as their associated volatilities, during the year, as can be seen in Figures 3-5, whereas such differences have been eliminated in Figures 6-8, which relate to the respective cruise seasons only. Figures 3-5 also give the daily and weekly differences in cruise passenger arrivals, as well as their respective volatilities, fro 1997-2006, while Figures 6-8 provide the cruise season counterparts. These figures also show the significant differences in the changes in cruise passenger arrivals and their volatilities throughout the year, as well as their respective high seasons.

On the basis of the time series data displayed in Figures 3-8 it is clear that there is persistence in the time-varying volatilities for cruise passenger arrivals, the daily difference in cruise passenger arrivals, and the weekly difference in cruise passenger arrivals for all three islands during the period 1997-2006, as well as for the respective cruise seasons. These conditional means and conditional volatilities will be discussed in the following section.

4. Conditional Mean and Conditional Volatility Models

The time series models to be estimated for the conditional means of daily cruise passenger arrivals during the year and in the high tourist season, as well as their conditional volatilities, are discussed below. As Figures 1, 2 and 3 illustrate, daily cruise passenger arrivals to the three islands show periods of high volatility followed by others of relatively low volatility. One implication of this persistent volatility behaviour is that the assumption of (conditionally) homoskedastic residuals is inappropriate (see, for example, Li, Ling and McAleer (2002) and McAleer (2005) for recent theoretical developments, and Bidarkota (2000) and Engle (2004) for practical developments).

McAleer, Chan and Marinova (2007) argue that, for a wide range of high frequency data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model, which was proposed by Engle (1982). When the time-varying conditional variance has both autoregressive and moving average components, this leads to the generalized ARCH(*p,q*), or GARCH(*p,q*), model of Bollerslev (1986). The lag structure of the appropriate GARCH model can be chosen by information criteria, such as those of Akaike and Schwarz, although it is very common to impose the widely estimated GARCH(1,1) specification in advance.

Consider the stationary AR(1)-GARCH(1,1) model for daily cruise passenger arrivals, 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 changes in daily cruise passenger arrivals) are given by:

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

and $\omega > 0, \alpha \geq 0$ 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 et al. (2007), Elie and Jeantheau (1995) and Jeantheau (1998) established that the log-moment condition was sufficient for consistency of the QMLE of an univariate GARCH(*p,q*) process (see Lee and Hansen (1994) for the proof in the case of GARCH(1,1)), and Boussama (2000) showed that the log-moment condition was sufficient for asymptotic normality. Based on these theoretical developments, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition, namely:

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

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

The effects of positive shocks (or upward movements in daily cruise passenger arrivals) on the conditional variance, h_t, are assumed to be the same as the negative shocks (or downward movements in daily cruise passenger arrivals) 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:

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

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

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

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

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

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

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

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

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

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

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

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 $|\, \beta \,| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iii) as the conditional (or standardized) shocks appear in equation (7), $|\, \beta \,| < 1$ would seem to be a sufficient condition for the existence of moments; (iv) in addition to being a sufficient condition for consistency, $|\, \beta \,| < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

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

The following is an interpretation of four different types of asymmetries in EGARCH(1,1) for daily cruise passenger arrivals (for further details, see Bartolomé et al. (2007)). Depending on the negative or positive slopes according to a positive or negative shock, these authors show that there are four possible scenarios of asymmetry in the EGARCH model, according to the restrictions on α and γ, as follows:

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

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

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

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

Figure 9. Type 1 Asymmetry: Low Season Financial Risk

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

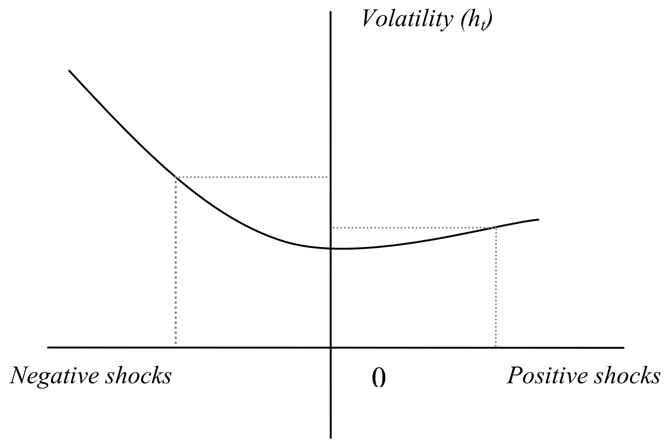


Figure 10. Type 2 Asymmetry: Overbooking Pressure on Carrying Capacity

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

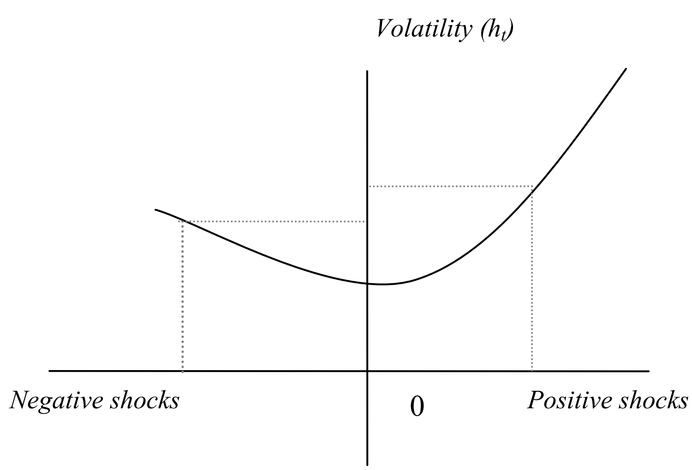


Figure 11. Type 3 Asymmetry: Tourism Saturation in High Season

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

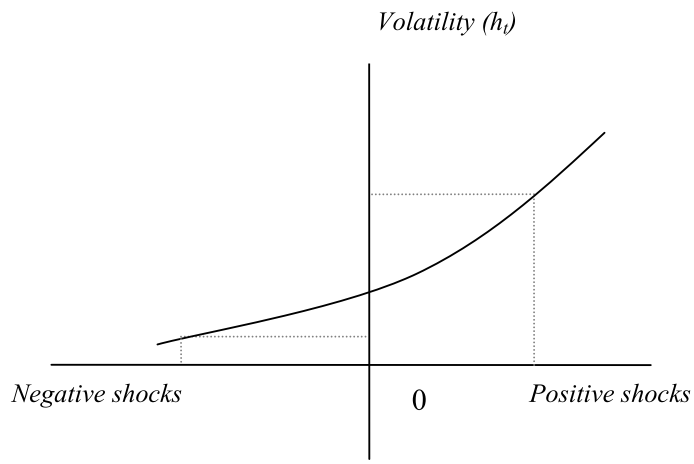
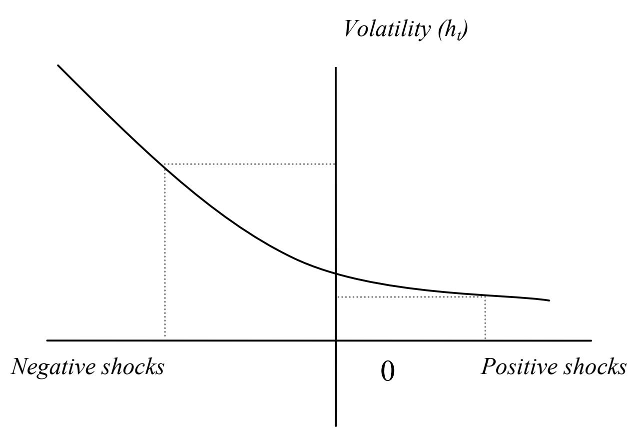


Figure 12. Type 4 Asymmetry: Leverage and Tourism Downturn

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



5. Estimated Models

Before proceeding to estimation of the model, the stationarity of cruise passenger arrivals needs to be tested. 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}, were calculated for the time series of daily cruise passenger arrivals to Palma, Ibiza and Mahon. 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 discussed above are obtained from the econometric software package EViews 5.0, and are reported in Table 7. The $MADF^{GLS}$ test, with a constant, and both with and without a deterministic trend, suggests that daily cruise passenger arrivals to Palma, Ibiza and Mahon are stationary. On the other hand, the MPP^{GLS} tests, suggest the possibility of a unit root in the series. For the high season series, the $MADF^{GLS}$ test shows that daily cruise passenger arrivals to Palma and Ibiza a are stationary, while the arrivals to Mahon appear to be non stationary. For this reason the conditional mean and conditional volatility models for Mahon in the high season may not be particularly reliable.

On the basis of the results in Table 7, the following conditional mean specifications are used to estimate daily cruise passenger arrivals, as well as their respective volatilities, using the GARCH(1,1), GJR(1,1) and EGARCH(1,1) models:

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

Model 2: $y_t = \phi_{00} + \phi_{01}\delta_H + \phi_1\delta_H y_{t-1} + \phi_2\delta_H y_{t-7} + \phi_3\delta_L y_{t-1} + \phi_4\delta_L y_{t-7} + \varepsilon_t.$

where the coefficient, ϕ_{01}, denotes the change in daily cruise passenger arrivals in the high season relative to the low season, the dummy variables δ_H and δ_L distinguish between the high and low cruise seasons in all three data sets, and are defined as follows:

$\delta_H = 1$ ($\delta_L = 0$) for the high cruise season,

$\delta_H = 0$ ($\delta_L = 1$) for the low cruise season.

Appropriate parametric restrictions imposed on Model 2, namely ϕ_{01}=ϕ_1-ϕ_3=ϕ_2-ϕ_4=0, will lead to Model 1. The analytical or numerical conditional log-likelihood function is maximized for each of Models 1 and 2 using either the BHHH or Marquardt algorithm in EViews 5.0.

The conditional mean (Model 1) and three conditional volatility models for daily cruise passenger arrivals to Palma, Ibiza and Mahon from 1997-2006 are given in Tables 8-10. Diagnostic checks in the form of the second moment condition, log-moment condition and type of asymmetry are also reported. It is striking that the conditional mean estimates are very different for each island. The one day lag effect ranges from 0.067 to 0.088 for Palma, from 0.153 to 0.168 for Ibiza, and from 0.159 to 0.205 for Mahon, while the one week lag effect ranges from 0.803 to 0.820 for Palma, from 0.369 to 0.434 for Ibiza, and from 0.250 to 0.298 for Mahon. This is in accordance with the data given in Figures 3-5. In particular the significant impact of the weekly lag for Palma arises precisely because of its position as a home port for Mediterranean cruises.

The conditional volatility estimates are very similar across the three models for each of Palma, Ibiza and Mahon. The GARCH(1,1) estimates for Palma suggest a low short run persistence of 0.104 and an explosive long run persistence of 1.006. However,the asymmetry coefficient, γ, in GJR(1,1) is found to be significant, so that positive and negative shocks of equal magnitude to daily cruise passenger arrivals affect volatility differently. The asymmetry coefficient, γ, for EGARCH(1,1) is also significant which is consistent with the empirical finding for its GJR counterpart. The parametric restrictions on EGARCH(1,1) suggest Type 3 Asymmetry, namely tourism saturation in the high season, so that an expansion of daily cruise passenger arrivals might prove difficult given present capacity. As the second moment condition is satisfied for GJR(1,1) and the log-moment condition is satisfied for GARCH(1,1), the QMLE are consistent and asymptotically normal, the estimates are sensible, and inferences are valid.

For Ibiza and Mahon, the estimates in Tables 9 and 10 are such that the short run persistence (long run persistence) for GARCH(1,1) are 0.125 and 0.126 (1.026 and 1.021), respectively. However the GJR(1,1) and EGARCH(1,1) estimates for Ibiza in Table 9 suggest an asymmetric response to positive and negative shocks of equal magnitude. The GJR(1,1) and EGARCH(1,1) estimates for Mahon are similar to those for Palma in that volatility is found to respond asymmetrically to positive and negative shocks of equal magnitude. The parametric restrictions on EGARCH(1,1) for Ibiza suggest Type 1 Asymmetry, namely low season financial risk, whereas for Mahon it is Type 4 asymmetry, namely leverage tourism downturn. In each case it would seem that the number of daily cruise passenger arrivals could be increased given present capacity. As the log-moment condition is satisfied for GARCH(1,1) and GJR(1,1), the QMLE have the desired asymptotic properties, the estimates are sensible, and the associated inferences are valid.

The conditional mean (Model 2) and three conditional volatility models for daily cruise passenger arrivals to Palma, Ibiza and Mahon from 1997-2006 are given in Tables 11-13. The primary purpose of Model 2 is to distinguish between daily cruise passenger arrivals in the high and low seasons for each island. The estimates that allow for differences between the high and low seasons in Tables 11-13 are significantly different from those given in Tables 8-10, in which seasonal differences are not accommodated. In the absence of dynamic effects, the conditional mean estimates for Palma in Table 11 range from 72 to 77 daily cruise passenger arrivals in the low season, which increase by 220 to 244 in the high season; for Ibiza in Table 12, daily cruise passenger arrivals range from 12 to 15 in the low season, which increase by 79 to 134 in the high season; and for Mahon in Table 13, daily cruise passenger arrivals range from 10 to 25 in the low season, which increase by 265 to 400 in the high season.

In Table 11, the one day lagged effect of cruise passenger arrivals is very similar and close to zero for the three volatility models for Palma, but the one week lagged effects are very different for the high and low seasons. In particular, the high season weekly lagged effect ranges from 0.839 to 0.849, whereas the low season weekly lagged effect ranges from 0.340 to 0.388. The daily and weekly lagged effects for Ibiza in Table 12 also differ between the high and low seasons, with the weekly lagged effect across the three conditional volatility models being particularly prominent. Although the daily and weekly lagged effects for Mahon in Table 13 also differ between the high and low seasons, the lagged effects are clearly more evident in the low rather than the high season.

Of the conditional volatility estimates for the three islands in Tables 11-13, the GJR(1,1) model suggests a symmetric response of positive and negative shocks of equal magnitude to daily cruise passenger arrivals for Palma, whereas its EGARCH(1,1) counterpart suggests an asymmetric response; the GJR(1,1) model suggests an asymmetric response of positive and negative shocks of equal magnitude to daily cruise passenger arrivals for Ibiza, whereas its EGARCH(1,1) counterpart suggests a symmetric response; whereas the GJR(1,1) and EGARCH(1,1) models suggest asymmetric responses of positive and negative shocks of equal magnitude to daily cruise passenger arrivals for Mahon. The parametric restrictions on EGARCH(1,1) for Palma, Ibiza and Mahon suggest Type 2, Type 1 and Type 1 Asymmetry, respectively, namely overbooking pressure on carrying capacity or low season financial risk. As the log-moment condition is satisfied for both GARCH(1,1) and GJR(1,1), for all three islands, the QMLE are consistent and asymptotically normal, and inferences are valid.

As could be seen from Figures 3-5, there are significant differences in the daily cruise passenger arrivals between the high and low seasons, which are May to October for Palma and June to September for Ibiza and Mahon. For this reason, Model 1 is re-estimated for the three islands using data for the cruise (or high) season only. The one day lagged effect of cruise passenger arrivals for all three islands is very close to zero, being insignificant in all three cases for Palma, in two cases for Ibiza, and in one case for Mahon. On the other hand, the one week lagged effect is significant for Palma at between 0.845 and 0.853, and is also significant for Ibiza at between 0.419 and 0.450. However, the one week lagged effect is not significant in any case for Mahon.

The conditional volatility estimates for Palma using only the high season data suggest a symmetric response to positive and negative shocks of equal magnitude for both Palma and Ibiza, using the GJR(1,1) and EGARCH(1,1) models. However, the GJR(1,1) model for Mahon suggests an asymmetric response, whereas its EGARCH(1,1) counterpart suggests a symmetric response to positive and negative shocks. The parametric restrictions on EGARCH(1,1) for both Palma, and Ibiza suggest Type 2 Asymmetry, namely overbooking pressure on carrying capacity. In five of six cases, the second moment condition is satisfied for GARCH(1,1) and GJR(1,1), so that the QMLE are consistent and asymptotically normal, and the inferences based on such estimates are valid.

Table 17 gives the likelihood ratio tests of constancy of coefficients in the high and low seasons. The null hypothesis in each case is Model 1, which can be obtained from the alternative hypothesis, Model 2, under the parametric restrictions given as $\phi_{01}=\phi_1-\phi_3=\phi_2-\phi_4=0$. Each set of nine calculated likelihood ratio test statistics for the three islands and the three conditional volatility models rejects the constancy of coefficients in the high and low seasons. Therefore, there is a clear difference between the impact of daily and weekly lagged effects in explaining cruise passenger arrivals in the high and low tourist seasons.

6. Concluding Remarks

As the fastest growing sector within the international tourism industry, having grown at roughly double the rate of international tourism as a whole, the cruise liner business has had impressive growth in the North American and European markets. Cruise passengers typically have higher than average incomes, are usually over 50 years of age, have greater flexibility in their choice of leisure time, and come from North America. For port management purposes, as well as for transport policy, it is essential to be able to forecast accurately cruise passenger arrivals and their variability. In the presence of time-varying variances (or volatility), it is crucial to model such volatility in order to provide sensible forecast intervals in addition to the forecast themselves.

Time-varying volatility in port management is important because governments and businesses need to be aware of the uncertainty associated with the number of cruise passenger arrivals and their associated growth. In calculating income elasticities, port taxes and tourist taxes, it is essential to obtain accurate estimates of cruise passenger arrivals and their volatility. Moreover, 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 cruise passenger arrivals for effective crisis management plans, including different forms of co-operation among ports facing similar shocks. In short, appropriate models are required to enable optimal private and public decision making in designing ports for cruise ships.

Daily cruise passenger arrivals data for the three major ports in the Balearic Islands, Spain, namely Palma, Ibiza and Mahon, for the period 1997-2006, as well as for the high cruise season for each island, were analyzed using alternative conditional mean and conditional volatility models in order to provide empirical support for purposes of optimal decision making.

Four different types of asymmetries were analyzed according to the positive and negative shocks to daily cruise passenger arrivals, as well as from distinctions between the high and low cruise seasons. The estimates of cruise passenger arrivals and their volatility were generally found to be sensible and to have valid statistical properties. Likelihood ratio tests of the constancy of coefficients in the high and low cruise seasons indicated that the weekly delayed response of cruise passenger arrivals differ significantly spatially across the three islands and temporally across the two seasons.

Given the present cruise berth capacity for each major port of the three islands, it is important for port authorities to forecast cruise passenger arrivals and their volatility using appropriate time series models. Future research will incorporate forecasts of both income and age distributions to predict daily cruise passenger arrivals more accurately.

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Figure 2: Yearly Cruise Passenger Arrivals to the Balearics from 1997-2006

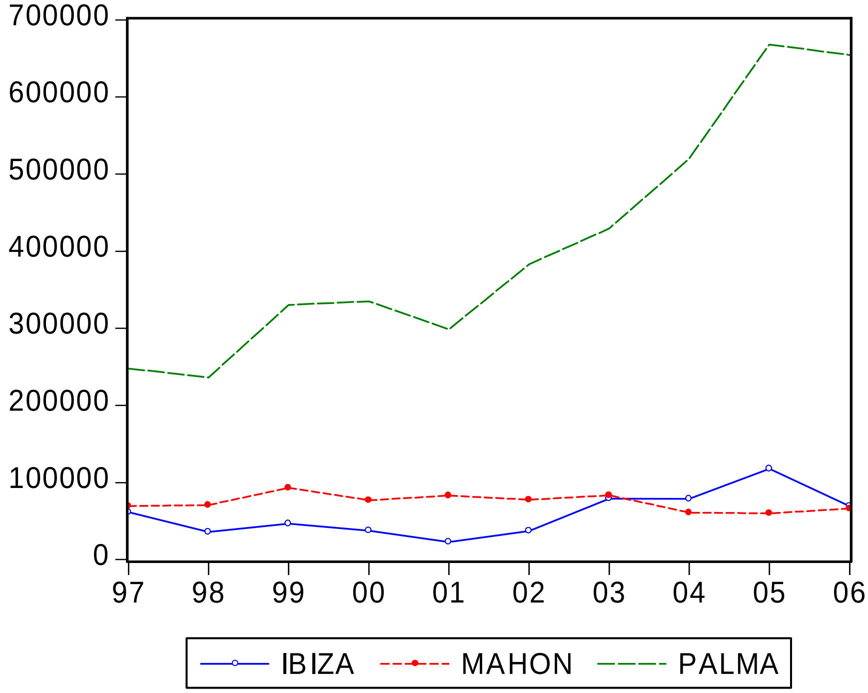

Figure 3: Daily Cruise Passenger Arrivals to Palma for 1997-2006

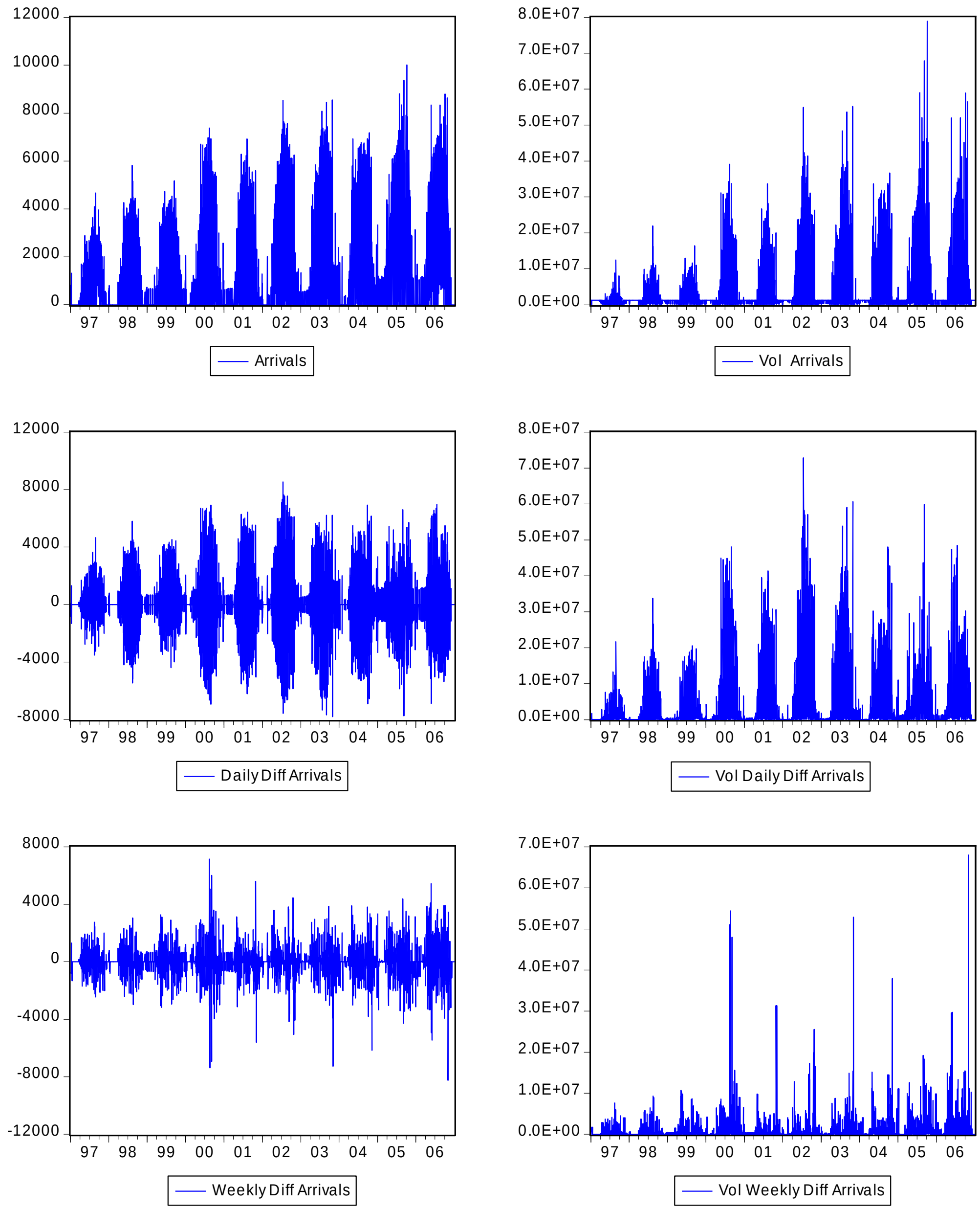

Figure 4: Daily Cruise Passenger Arrivals to Ibiza for 1997-2006

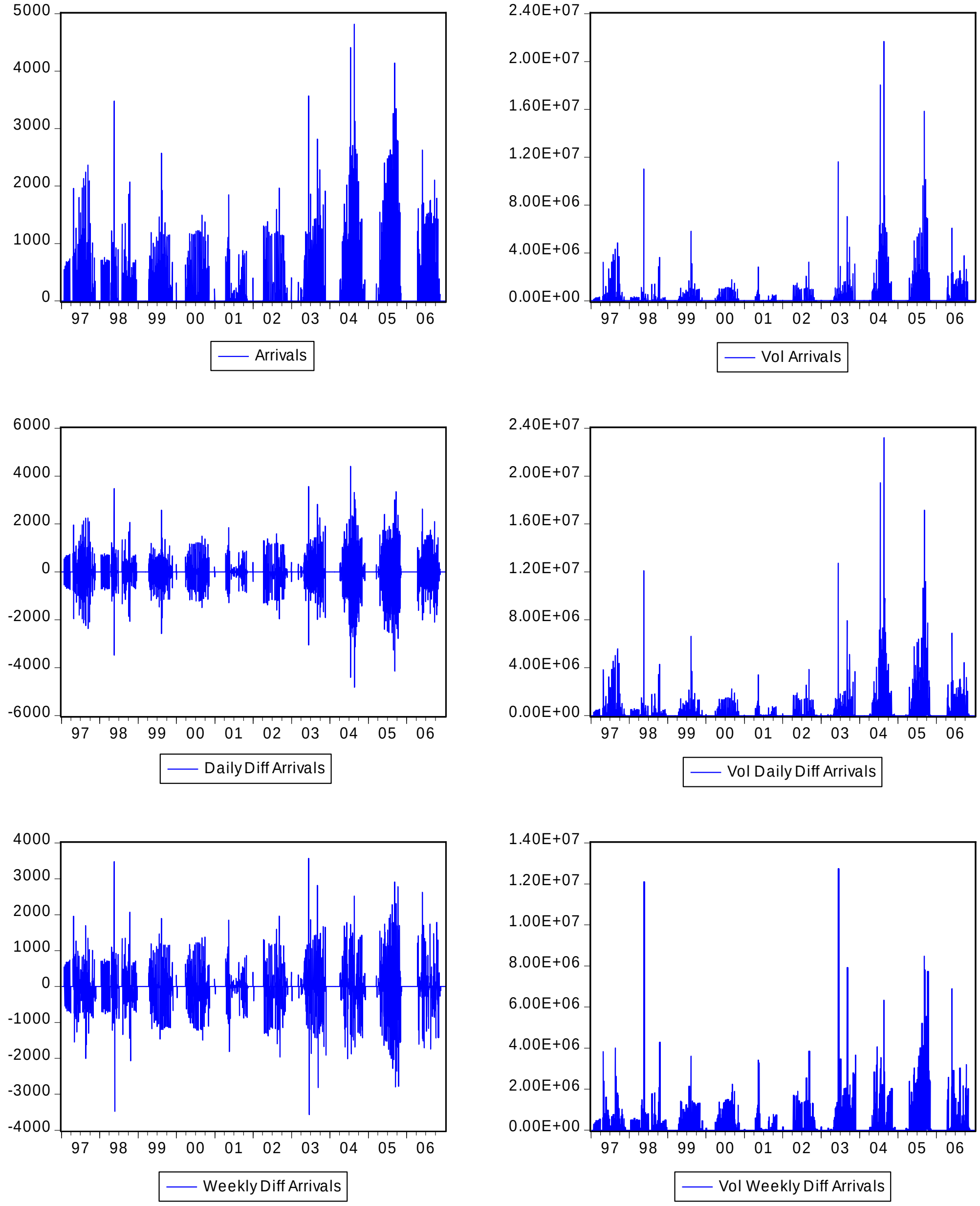

Figure 5 : Daily Cruise Passenger Arrivals to Mahon for 1997-2006

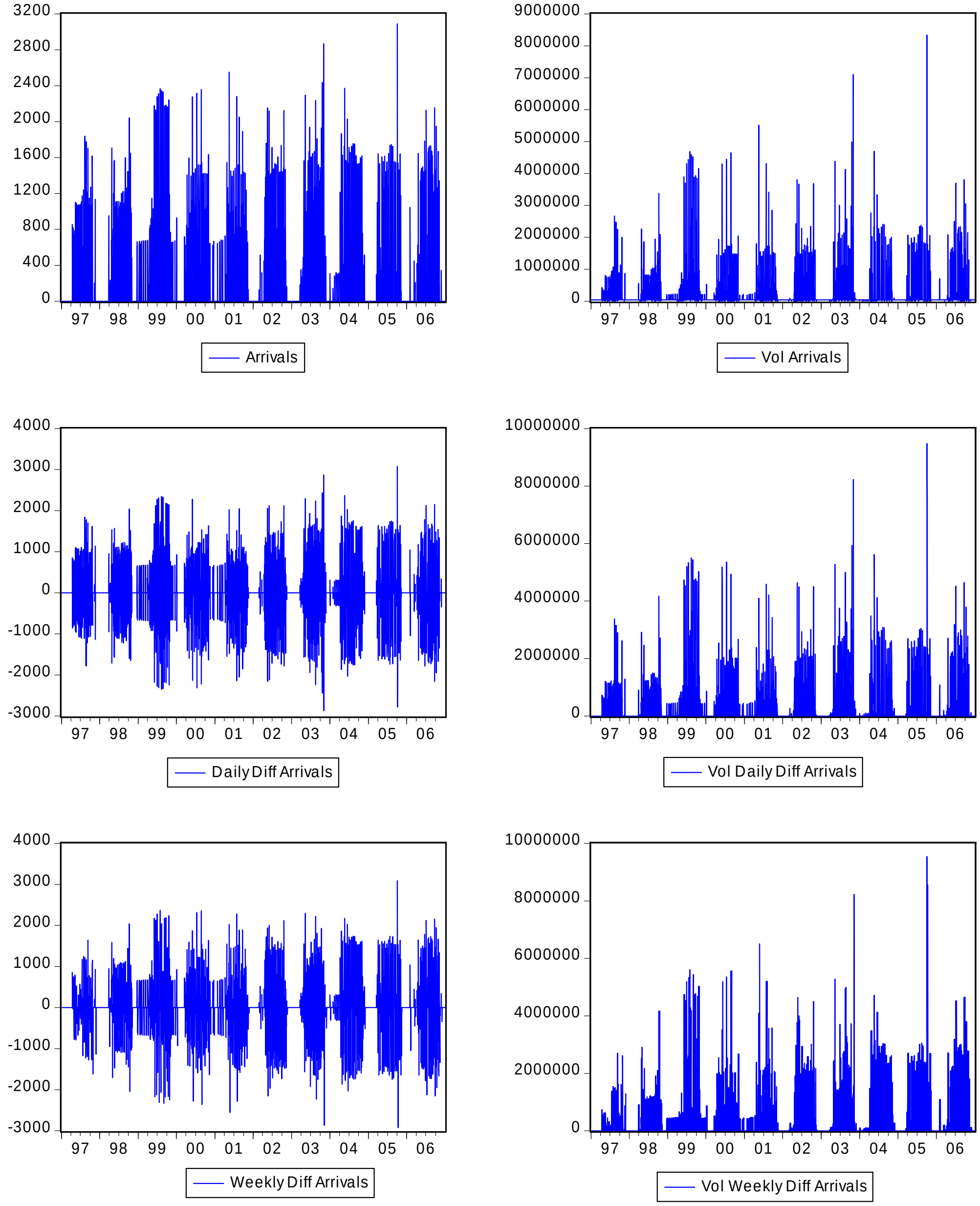

Figure 6: Daily Cruise Passenger Arrivals to Palma during the Cruise Season, May to October

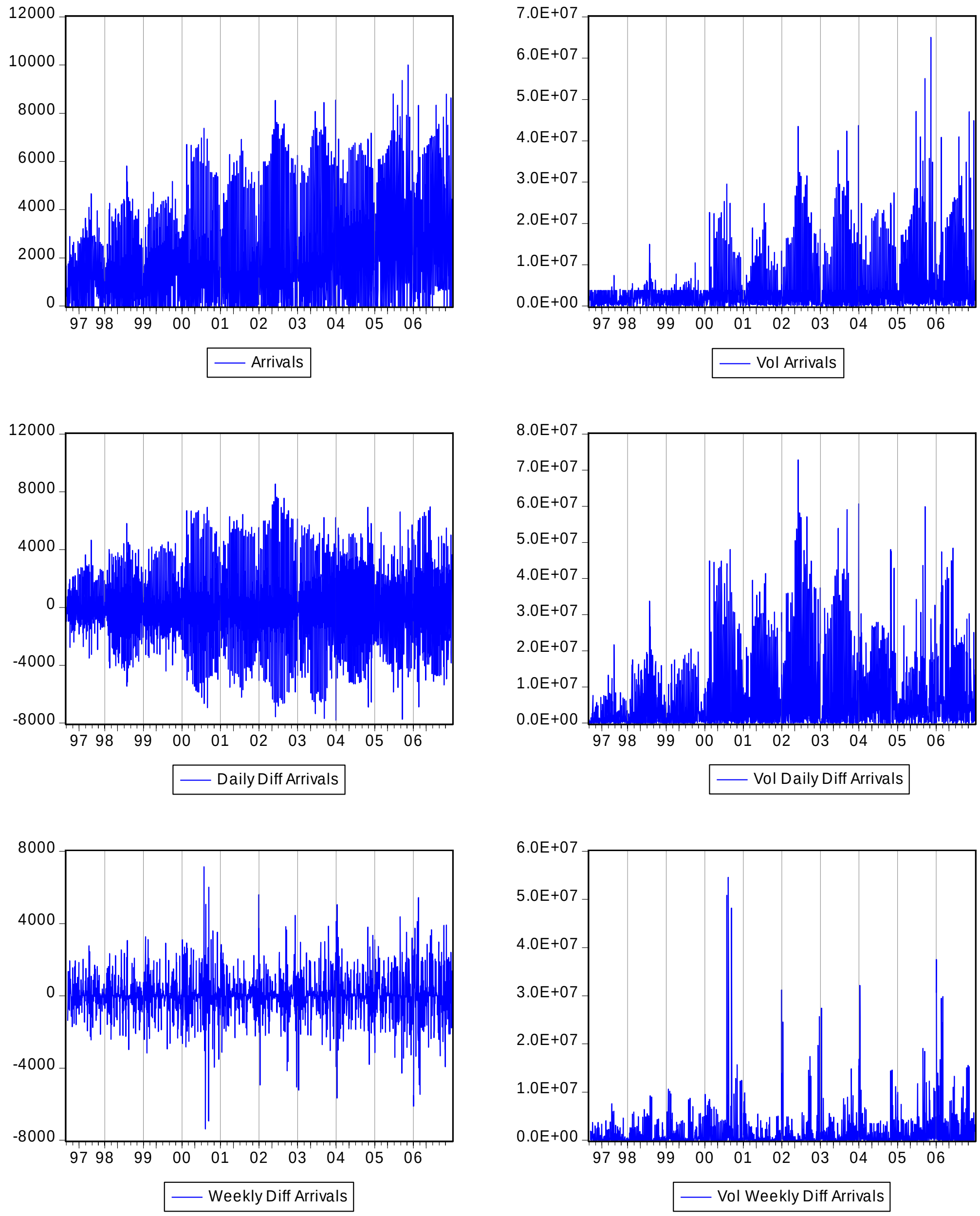

Figure 7: Daily Cruise Passenger Arrivals to Ibiza during the Cruise Season, June to September

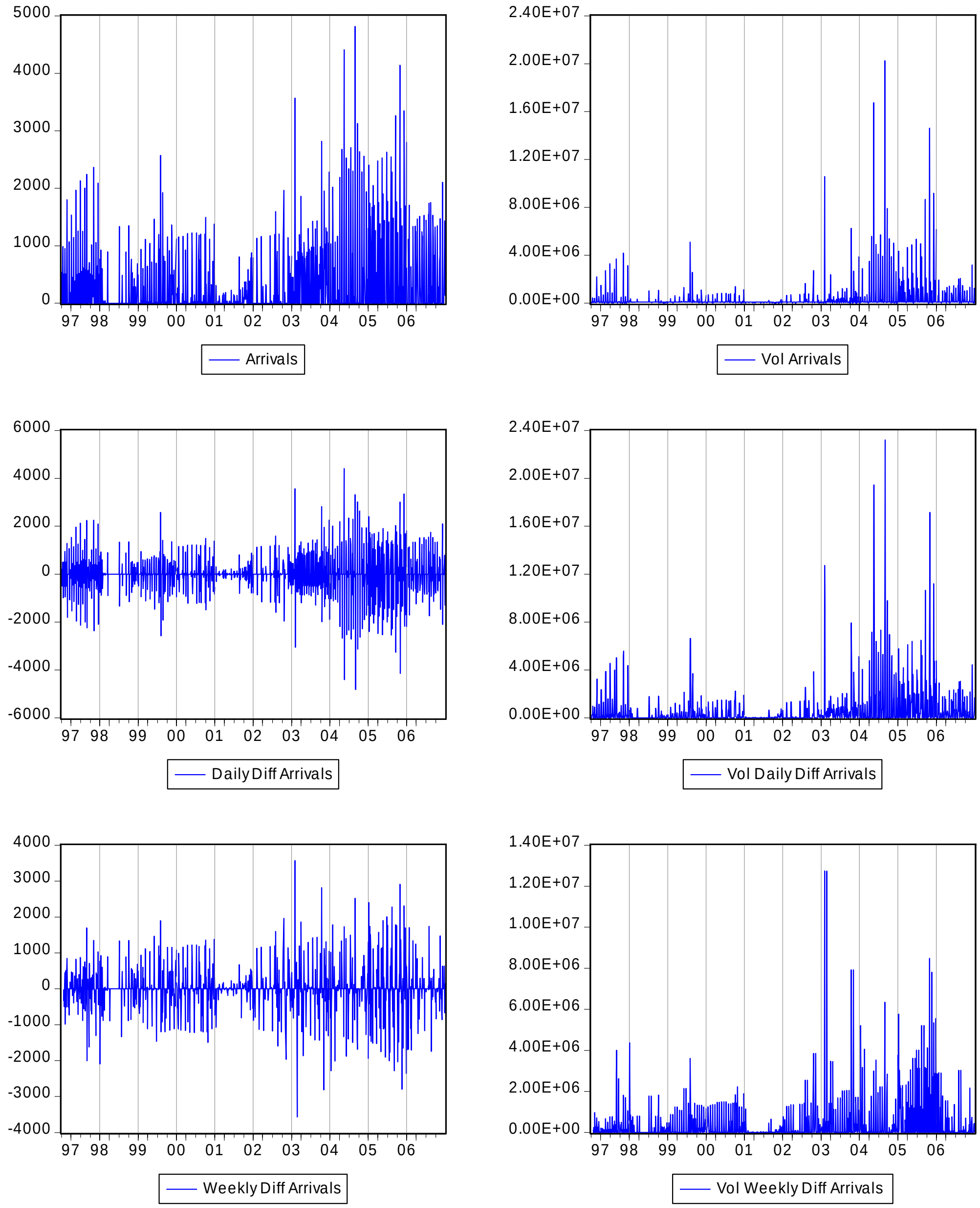

Figure 8: Daily Cruise Passenger Arrivals to Mahon during the Cruise Season, June to September

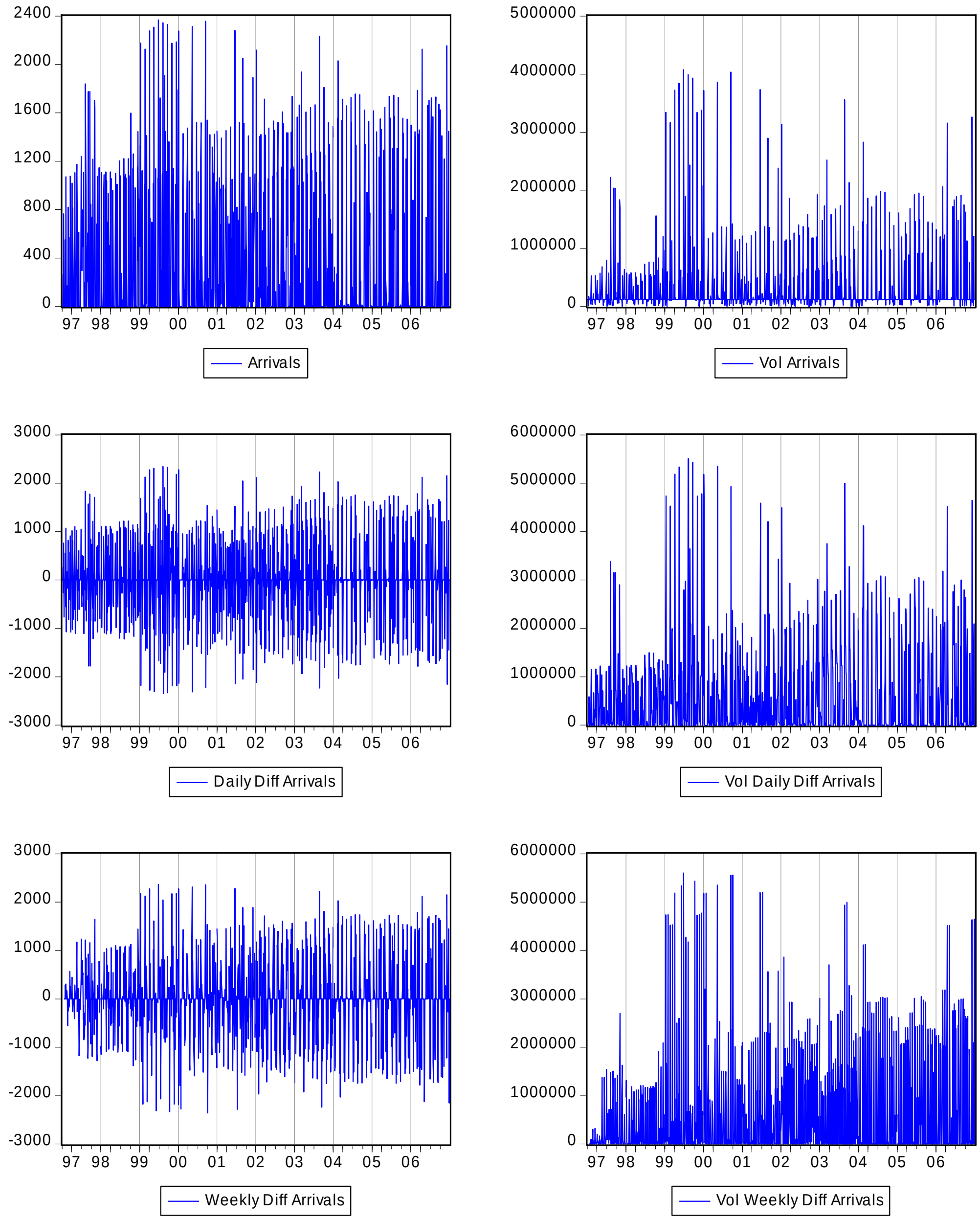

Table 5. Descriptive Statistics of Daily Cruise Passenger Arrivals, 1997-2006

Statistics	Palma	Ibiza	Mahon
Mean	1123.2	160.7	202.7
Median	264.5	0	0
Maximum	10005	4817	3089
Minimum	0	0	0
Std. Dev.	1715.89	436.30	451.19
Skewness	1.93	3.83	2.44
Kurtosis	6.46	22.23	8.62
J-B	4111.3	65215.8	8423.7
Prob.	0	0	0

Note:
The number of observations is 3,652.

Table 6. Descriptive Statistics of Daily Cruise Passenger Arrivals during the Cruise Season

Statistics	Palma	Ibiza	Mahon
Mean	1940.4	316.61	348.5
Median	1342	0	0
Maximum	10005	4817	2368
Minimum	0	0	0
Std. Dev.	2003.3	607.5	566.3
Skewness	1.20	2.66	1.51
Kurtosis	3.75	12.05	4.19
J-B	484.6	5595.5	534.9
Prob.	0	0	0

Note:
The numbers of observations are 1,840 for Palma and 1,220 for Ibiza and Mahon.

Table 7. Unit Root Tests

Daily cruise passenger arrivals	MADF^{GLS}		MPP^{GLS}		
	Z=(1, t)	Z=(1)	Z=(1, t)	Z=(1)	Lags
Palma	-4.067***	-3.649***	-13.790	-12.015**	29
Ibiza	-3.701***	-2.861***	-6.273	-5.138	27
Mahon	-3.650***	-2.800***	-6.527	-5.096	29
HS Palma, May-Oct	-3.088**	-1.817*	-1.861	-0.851	20
HS Ibiza, June-Sept	-2.951**	-2.872***	-2.485	-2.447	20
HS Mahon, June-Sept	-2.517	-1.486	-1.929	-1.521	22

Notes:
HS denotes High (Cruise) Season.
(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 8. Conditional Mean and Conditional Volatility Models for Palma, 1997-2006

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	58.666 (10.047)	60.604 (10.459)	59.797 (10.768)
ϕ_1	0.088 (0.012)	0.067 (0.012)	0.075 (0.012)
ϕ_2	0.803 (0.013)	0.820 (0.013)	0.815 (0.014)
ω	5645.2 (2279.72)	4213.48 (1521.02)	0.277 (0.072)
GARCH/GJR α	0.104 (0.014)	0.117 (0.015)	--
GJR γ	--	-0.132 (0.017)	--
GARCH/GJR β	0.902 (0.012)	0.935 (0.010)	--
EGARCH α	--	--	0.110 (0.025)
EGARCH γ	--	--	0.140 (0.018)
EGARCH β	--	--	0.973 (0.006)
Diagnostics			
Second moment	1.006	0.986	--
Log-moment	-0.017	-0.013	--
Asymmetry	--	--	Type 3
Log likelihood	-29477.77	-29407.00	-29372.73

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

Table 9. Conditional Mean and Conditional Volatility Models for Ibiza, 1997-2006

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	18.182 (2.591)	18.373 (3.720)	14.023 (4.950)
ϕ_1	0.153 (0.026)	0.168 (0.026)	0.165 (0.024)
ϕ_2	0.434 (0.031)	0.369 (0.027)	0.385 (0.031)
ω	773.848 (368.77)	745.46* (399.56)	0.158* (0.117)
GARCH/GJR α	0.125 (0.025)	0.081 (0.024)	--
GJR γ	--	0.438* (0.287)	--
GARCH/GJR β	0.902 (0.017)	0.886 (0.024)	--
EGARCH α	--	--	0.342 (0.108)
EGARCH γ	--	--	-0.118* (0.104)
EGARCH β	--	--	0.973 (0.011)
Diagnostics			
Second moment	1.026	1.186	--
Log-moment	-0.029	-0.029	--
Asymmetry	--	--	Type 1*
Log likelihood	-25614.92	-25590.11	-25572.24

Notes:
Y_t is the number of daily cruise 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.

Table 10. Conditional Mean and Conditional Volatility Models for Mahon, 1997-2006

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	28.049 (3.072)	28.651 (4.204)	15.269 (9.171)
ϕ_1	0.205 (0.021)	0.159 (0.023)	0.161 (0.023)
ϕ_2	0.298 (0.023)	0.250 (0.026)	0.276 (0.030)
ω	923.877 (368.59)	257.28* (511.63)	0.077* (0.218)
GARCH/GJR α	0.126 (0.015)	0.057 (0.024)	--
GJR γ	--	1.027 (0.407)	--
GARCH/GJR β	0.895 (0.011)	0.872 (0.015)	--
EGARCH α	--	--	0.469 (0.090)
EGARCH γ	--	--	-0.298 (0.103)
EGARCH β	--	--	0.978 (0.017)
Diagnostics			
Second moment	1.021	1.021	--
Log-moment	-0.024	-0.025	--
Asymmetry	--	--	Type 4
Log likelihood	-26453.17	-26398.76	-26421.45

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

Table 11. Conditional Mean and Conditional Volatility Models for Palma, 1997-2006

Model 2: $y_t = \phi_{00} + \phi_{01}\delta_H + \phi_1\delta_H y_{t-1} + \phi_2\delta_H y_{t-7} + \phi_3\delta_L y_{t-1} + \phi_4\delta_L y_{t-7} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_{00}	74.780 (10.453)	77.010 (10.685)	71.885 (17.245)
ϕ_{01}	243.57 (48.027)	219.692 (44.813)	231.11 (45.695)
ϕ_1	0.007* (0.013)	0.009* (0.014)	0.012* (0.014)
ϕ_2	0.842 (0.014)	0.849 (0.014)	0.839 (0.015)
ϕ_3	0.092 (0.034)	0.086 (0.033)	0.084 (0.036)
ϕ_4	0.340 (0.039)	0.362 (0.039)	0.388 (0.036)
ω	4391.32 (1804.70)	3983.65 (1797.91)	0.193 (0.066)
GARCH/GJR α	0.103 (0.015)	0.115 (0.017)	--
GJR γ	--	-0.048* (0.033)	--
GARCH/GJR β	0.905 (0.013)	0.911 (0.012)	--
EGARCH α	--	--	0.184 (0.032)
EGARCH γ	--	--	0.061 (0.026)
EGARCH β	--	--	0.976 (0.006)
Diagnostics			
Second moment	1.008	1.001	--
Log-moment	-0.016	-0.015	--
Asymmetry	--	--	Type 2
Log likelihood	-29245.78	-29240.30	-29203.89

Notes:
Y_t is the number of daily cruise passenger arrivals to Palma.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant.
δ_H is the dummy variable for the high season from May to October.
δ_L is the dummy variable for the low season from November to April.

Table 12. Conditional Mean and Conditional Volatility Models for Ibiza, 1997-2006

Model 2: $y_t = \phi_{00} + \phi_{01}\delta_H + \phi_1\delta_H y_{t-1} + \phi_2\delta_H y_{t-7} + \phi_3\delta_L y_{t-1} + \phi_4\delta_L y_{t-7} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_{00}	13.069 (2.378)	14.917 (4.083)	11.862* (6.228)
ϕ_{01}	133.692 (27.077)	85.873 (23.235)	79.010 (20.041)
ϕ_1	0.079 (0.039)	0.074 (0.037)	0.085 (0.033)
ϕ_2	0.500 (0.042)	0.423 (0.043)	0.474 (0.040)
ϕ_3	0.133 (0.047)	0.200 (0.044)	0.171 (0.039)
ϕ_4	0.293 (0.056)	0.288 (0.046)	0.291 (0.053)
ω	784.39 (388.57)	793.37* (433.48)	0.251* (0.193)
GARCH/GJR α	0.147 (0.022)	0.082 (0.027)	--
GJR γ	--	0.555 (0.245)	--
GARCH/GJR β	0.888 (0.015)	0.866 (0.023)	--
EGARCH α	--	--	0.393 (0.097)
EGARCH γ	--	--	-0.144* (0.083)
EGARCH β	--	--	0.962 (0.018)
Diagnostics			
Second moment	1.036	1.225	--
Log-moment	-0.035	-0.044	--
Asymmetry	--	--	Type 1*
Log likelihood	-25505.71	-25467.37	-25436.27

Notes:
Y_t is the number of daily cruise 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.
δ_H is the dummy variable for the high season from June to September.
δ_L is the dummy variable for the low season from October to May.

Table 13. Conditional Mean and Conditional Volatility Models for Mahon, 1997-2006

Model 2: $y_t = \phi_{00} + \phi_{01}\delta_H + \phi_1\delta_H y_{t-1} + \phi_2\delta_H y_{t-7} + \phi_3\delta_L y_{t-1} + \phi_4\delta_L y_{t-7} + \varepsilon_t$

Parameters	GARCH	GJR	EGARCH
ϕ_{00}	22.302 (3.089)	24.943 (3.958)	9.359* (7.941)
ϕ_{01}	399.310 (30.230)	265.081 (28.807)	284.58 (29.34)
ϕ_1	-0.032* (0.029)	-0.051* (0.031)	-0.072 (0.029)
ϕ_2	0.035* (0.026)	0.053 (0.023)	0.054 (0.024)
ϕ_3	0.174 (0.032)	0.217 (0.032)	0.228 (0.035)
ϕ_4	0.269 (0.038)	0.268 (0.032)	0.289 (0.036)
ω	1081.55 (406.44)	911.963 (423.134)	0.407 (0.160)
GARCH/GJR α	0.134 (0.017)	0.059 (0.028)	--
GJR γ	--	0.667 (0.273)	--
GARCH/GJR β	0.884 (0.014)	0.860 (0.022)	--
EGARCH α	--	--	0.398 (0.089)
EGARCH γ	--	--	-0.201 (0.084)
EGARCH β	--	--	0.949 (0.015)
Diagnostics			
Second moment	1.019	1.252	--
Log-moment	-0.030	-0.057	--
Asymmetry	--	--	Type 1
Log likelihood	-26314.62	-26270.72	-26263.88

Notes:
Y_t is the number of daily cruise passenger arrivals to Mahon.
Numbers in parentheses are standard errors.
(*) indicates the coefficient is not significant at the 5% level; otherwise, all estimates are significant.
δ_H is the dummy variable for the high season from June to September.
δ_L is the dummy variable for the low season from October to May.

Table 14. Conditional Mean and Conditional Volatility Models for Palma during the Cruise Season, May to October

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	279.289 (38.904)	288.96 (38.83)	287.173 (37.509)
ϕ_1	0.012* (0.013)	0.011* (0.013)	0.009* (0.014)
ϕ_2	0.845 (0.014)	0.851 (0.013)	0.853 (0.014)
ω	34828.59 (11420)	34612.8 (13157.5)	0.332 (0.152)
GARCH/GJR α	0.057 (0.014)	0.079 (0.018)	--
GJR γ	--	-0.053* (0.035)	--
GARCH/GJR β	0.919 (0.020)	0.922 (0.022)	--
EGARCH α	--	--	0.127 (0.041)
EGARCH γ	--	--	0.055* (0.029)
EGARCH β	--	--	0.971 (0.011)
Diagnostics			
Second moment	0.976	0.974	--
Log-moment	-0.030	-0.030	--
Asymmetry	--	--	Type 2*
Log likelihood	-15476.78	-15472.90	-15480.46

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

Table 15. Conditional Mean and Conditional Volatility Models for Ibiza during the Cruise Season, June to September

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	116.68 (13.22)	114.42 (14.188)	162.73 (17.150)
ϕ_1	0.067* (0.029)	0.080 (0.029)	0.024* (0.027)
ϕ_2	0.441 (0.037)	0.419 (0.037)	0.450 (0.041)
ω	967.07* (787.06)	-138.221* (1260.23)	21.187 (1.729)
GARCH/GJR α	0.031 (0.007)	0.023 (0.011)	--
GJR γ	--	0.070* (0.060)	--
GARCH/GJR β	0.967 (0.009)	0.965 (0.009)	--
EGARCH α	--	--	0.204 (0.080)
EGARCH γ	--	--	0.035* (0.086)
EGARCH β	--	--	-0.702 (0.140)
Diagnostics			
Second moment	0.998	1.023	--
Log-moment	-0.004	0.001	--
Asymmetry	--	--	Type 2*
Log likelihood	-9239.95	-9238.37	-9321.17

Notes:
Y_t is the number of daily cruise 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.

Table 16. Conditional Mean and Conditional Volatility Models for Mahon during the Cruise Season, June to September

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

Parameters	GARCH	GJR	EGARCH
ϕ_0	332.815 (17.904)	329.536 (21.633)	352.016 (22.609)
ϕ_1	-0.047 (0.010)	-0.054 (0.019)	-0.044* (0.023)
ϕ_2	0.045* (0.027)	0.052* (0.027)	0.029* (0.027)
ω	87604.72 (4276.22)	70883.66 (3805.72)	19.156 (2.376)
GARCH/GJR α	-0.071 (0.019)	-0.065 (0.011)	--
GJR γ	--	0.174 (0.036)	--
GARCH/GJR β	0.799 (0.011)	0.808 (0.012)	--
EGARCH α	--	--	-0.333 (0.169)
EGARCH γ	--	--	0.041* (0.107)
EGARCH β	--	--	-0.491 (0186)
Diagnostics			
Second moment	0.729	0.834	--
Log-moment	NA	NA	--
Asymmetry	--	--	NA
Log likelihood	-9393.86	-9392.75	-9403.58

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

Table 17. Likelihood Ratio Tests of Constant Coefficients in High and Low Seasons

H_0: Model 1 **H_1: Model 2**	**GARCH**	**GJR**	**EGARCH**
Palma	463.98	333.4	337.68
Ibiza	217.42	245.48	271.94
Mahon	277.10	256.08	316.14

Notes:

Models 1 and 2 are estimated using daily cruise passenger arrivals from 1997 to 2006. The null hypothesis is Model 1, namely H_o: $\phi_{01}=\phi_1-\phi_3=\phi_2-\phi_4=0$.

As the critical value of the likelihood ratio test statistic at the 5% level is $\chi^2(3) = 7.815$, all test statistics are significant.