# VOLATILITY AND SEASONALITY OF TOURISM DEMAND IN PORTUGAL*

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## 1. INTRODUCTION

Tourism is an important economic activity of Portugal. According to preliminary data from the Portuguese Office for National Statistics (INE, 2009), tourism generated in 2008 about 5% of the Economy's Gross Value Added, corresponding to approximately 7.3 billion euros. The 2008 Report on Competitiveness of Travel and Tourism, ranked Portugal 15th from a list of 130 countries in terms of tourism industry competitiveness. Overall, Portugal climbed seven positions in relation to 2007 and four positions among all 27 EU countries (Portugal Digital, 2008). Amador and Cabral (2009) present a detailed analysis of the services industry in Portugal and show that this positive evolution has occurred in this sector in general and reveals a comparative advantage in the travel and tourism industry.

The main source countries of tourists to Portugal include Germany, Spain, France, the Netherlands and the United Kingdom, with these countries accounting for more than four-fifths of total inbound tourists. Spain is responsible for almost half of foreign tourism. In 2008, these countries represented over 65% of total tourism revenue, in 1990, 58% and in 1970, 44%. The United Kingdom was the main generator of revenue in 2008 having reached 1 640 375 thousand euros, followed by France with 1 200 581 thousand euros. Domestic tourism demand is of growing interest and an important focus of the 2006-2015 National Strategic Plan for tourism is precisely to "accelerate the growth of domestic tourism".

Seasonality is an important feature of tourism and in particular of Portuguese tourism (Baum e Lundtorp, 2001). It is in the warmer months that the country is most sought by tourists and the number of nights spent in hotel establishments increases. However, although the tourism industry looks to diversification in terms of supply, seasonality is an important feature of tourism and should be taken into account when developing this area of research.

In addition, nonstationarity and conditional heteroscedasticity (high and low volatility movements) are other important characteristics of tourism series. Volatility is considered by many researchers as an unpredictable measure of variation intensity. These variations are normally associated to unexpected

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events typically known as “news shocks” (Shareef and McAleer, 2005 and Kim and Wong, 2006). For instance, among several factors responsible for changes in tourism patterns, are global terrorism, economic changes in the tourism source countries, exchange rate volatility, tourist health and safety in the destination and unexpected national and international political changes.

The main objective of this paper is to analyse and model tourism demand series. Based on a range of existing models, we apply a symmetric model – the GARCH model (Engle, 1982 and Bollerslev, 1986) - and two asymmetric models – the GJR model (Glosten, Jagannathan and Rukle, 1993) and the EGARCH model (Nelson, 1991). The inclusion of the latter two is due to the fact that volatility may exhibit asymmetric behavior, *i.e.*, may display different responses to positive and negative shocks. The information that can be drawn from the application of these methodologies, especially in the current context of economic and financial instability we are experiencing, may be useful for macroeconomic analysis and forecasting.

This paper is structured as follows. Section 2 provides a brief overview of the volatility models used in the paper. Section 3 presents a description of the data and Section 4 estimation results for the volatility models. Section 5 summarizes the main conclusions.

## 2. DESCRIPTION OF VOLATILITY MODELS

An important characteristic of the behaviour of volatility in tourism demand series (similar to what happens in financial series) is that periods of high volatility may be followed by periods of low volatility and vice-versa. This type of behaviour is known in the literature as “Volatility Clustering”. This characteristic is directly related to leverage and asymmetry effects, *i.e.*, the response of volatility to shocks. The asymmetry effect indicates that volatility of a series is affected differently whether the news are positive or negative and the leverage effect indicates that volatility gets higher and more persistent as a response to negative shocks than to positive shocks. According to McAleer (2005): “A favourable comment can increase happiness momentarily, but a negative comment can last forever” (p. 237).

As will be seen below, there are models that are appropriate for situations where volatility presents symmetric behaviour, and models that fit situations in which volatility displays asymmetric behaviour. Consider the first group of models.

The Autoregressive Conditionally Heteroskedasticity (ARCH) model introduced by Engle (1982) looks to model the autoregressive structure of the linear time dependence that exists in the error variance of a time series of interest. An ARCH model of order q can be specified as,

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \tag{1}$$

where $\omega > 0$ and $\alpha_i \geq 0$, $i=1,\ldots,q$, $\sigma_t^2$ is the conditional variance, $\varepsilon_t = u_t \sigma_t$ and $u_t$ is an independent and identically distributed (iid) random variable.

This equation considers that the volatility of a series is a random variable influenced by past variability. It is a model that presents however limitations, such as imposition of the non-negativity of its parameters and the need to include a large number of lags to capture the volatility of the process.

Given these limitations, Bollerslev (1986) proposed a new structure known as generalized ARCH (GARCH). The general GARCH (*p, q*) model can be presented as,

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

where $\omega > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$ are sufficient conditions to ensure that the conditional variance, $\sigma_t^2$, is positive. The first sum corresponds to the GARCH component of order q and the second to the ARCH component of order *p*. The GARCH (1,1) model has proven to be sufficient to model the variance and has been widely used in the literature. In this case, equation 2 reduces to,

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 \tag{3}$$

where $\alpha$ measure the persistence of shocks in the short-run, and $(\alpha+\beta)$ reveals the degree of persistence of volatility in the long-run. To ensure that $\sigma_t^2$ is positive, $\omega > 0$, and $\alpha$ and $\beta$ must be non-negative (*i.e.* $\alpha \geq 0$, and $\beta \geq 0$). The sum of $\alpha$ and $\beta$ has to be below one to ensure the stationarity condition (*i.e.*, $\alpha + \beta < 1$).

The ARCH and GARCH models assume that volatility has symmetric behaviour *i.e.*, that it has the same behaviour for positive or negative shocks (good or bad news). However, in practice this is not always the case. This led Nelson (1991) to introduce the exponential GARCH model known in the literature as EGARCH model. The EGARCH (1,1) model, frequently found in the literature, has the following specification:

$$\log \sigma_t^2 = \omega + \beta \log \sigma_{t-1}^2 + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

In this case, given that the left-hand side of the equation is the logarithm of the conditional variance it is not necessary to impose non-negativity constraints on $\alpha$ and $\beta$. This model considers a multiplier effect (leverage effect) through the term $\varepsilon_{t-1}/\sigma_{t-1}$, that seeks to capture different impacts of positive and negative shocks on volatility. The leverage effect occurs if $\gamma<0$. The asymmetric effect, which is also considered by this term, is used to determine whether the market differentiates positive and negative effects. The asymmetric effect occurs if $\gamma\neq 0$ and is symmetric if $\gamma=0$. The persistence of the shock in this model is measured through $\beta$.

Glosten, Jagannathan e Runkle (1993) and Zakoian (1994) introduced the Threshold ARCH model or TARCH[1] model, which also considers the asymmetric effect of volatility. The most common model is the TARCH(1,1) that has the following specification:

(1) This model is also commonly known in the literature as GJR model.

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} \quad (5)$$

In this model $d_t=1$ if $\varepsilon_t$ is negative and zero otherwise. Again it is necessary that $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha+\gamma \geq 0$ to ensure that $\sigma_t^2$ is positive. Regarding the impact of news on volatility, it tends to increase with negative shocks (when $\varepsilon_{t-1}<0$) and decrease with positive shocks (when $\varepsilon_{t-1}>0$). As in the previous model the shock is asymmetric if $\gamma \neq 0$ and is symmetric if $\gamma=0$, but unlike the previous model the leverage effect occurs if $\gamma>0$. The short-run effect of positive shocks (good news) is measured through $\alpha$, and that of negative shocks (bad news) through $\alpha+\gamma$. The persistence of shocks in the short-run is measured as $\alpha+\gamma/2$ and in the long-run as $\alpha+\beta+\gamma/2$.

For a more detailed review of these models and others associated to the same topic see for example, Bollerslev, Engle and Nelson (1994), Li *et al*. (2002) and McAleer (2005) and for applications to tourism, Chan, Lim and McAleer (2005), Shareef and McAleer (2007) and Divino and McAleer (2008), among others.

## 3. DATA

The data used in this paper is monthly and covers the period from January 1976 to December 2006, constituting a sample of 372 observations for each of the source countries of tourists to Portugal, *i.e.* Germany, Spain, France, the Netherlands and the United Kingdom. We also consider domestic demand in our analysis. To measure tourism demand we have chosen the “Number of nights spent in hotel establishments”. The time series were obtained from one of the main publications of the ex-*Direcção Geral do Turismo* – “O Turismo em ….” (several years) and from *INE* (the Portuguese Office for National Statistics) – “Estatísticas do Turismo” (several years). Graphical representation of the series in levels and natural logarithms are presented in Charts 1 and 2.

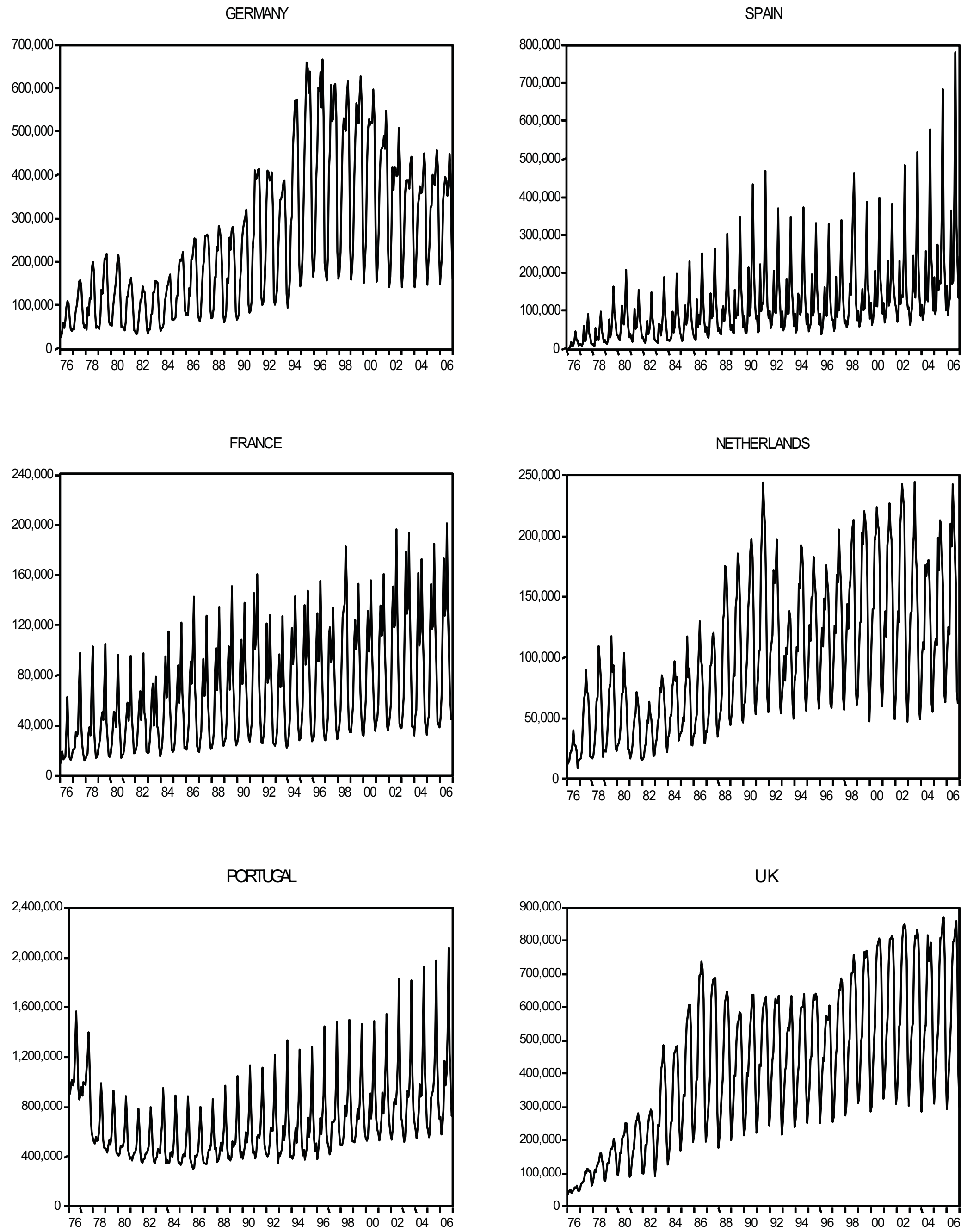
Despite the existence of stages of growth and decline, all series exhibit a strong seasonal pattern. In the case of Portugal, the values of the first two years are slightly overstated. This is due to the fact that many individuals returning from the ex-Portuguese colonies during the decolonization process had been temporarily housed in hotels. Table 1 presents some descriptive statistics of the series under study.

From Table 1, it can be observed that the standard deviation is high when compared to the mean (coefficient of variation). Of all countries considered, Portugal has the lowest coefficient of variation, meaning that data are less dispersed, thus suggesting a more stable demand. The asymmetry and kurtosis are typically analyzed with reference to the normal distribution. The normal distribution is symmetric (the measure of asymmetry is zero) and mesocurtic (*i.e.* the value of the measure of kurtosis is 3). Hence, taking these values as reference and considering the results in Table 1 obtained for the various countries under analysis, we observe that asymmetry is always positive and from the value for kurtosis we conclude for a platicurtic distribution (a flatter distribution than the normal, *i.e.* the values are more dispersed from the mean) for Germany, France, the Netherlands and the United

### Chart 1

**TOURISM DEMAND OF THE MAIN SOURCE COUNTRIESTURISTAS**

Tourists

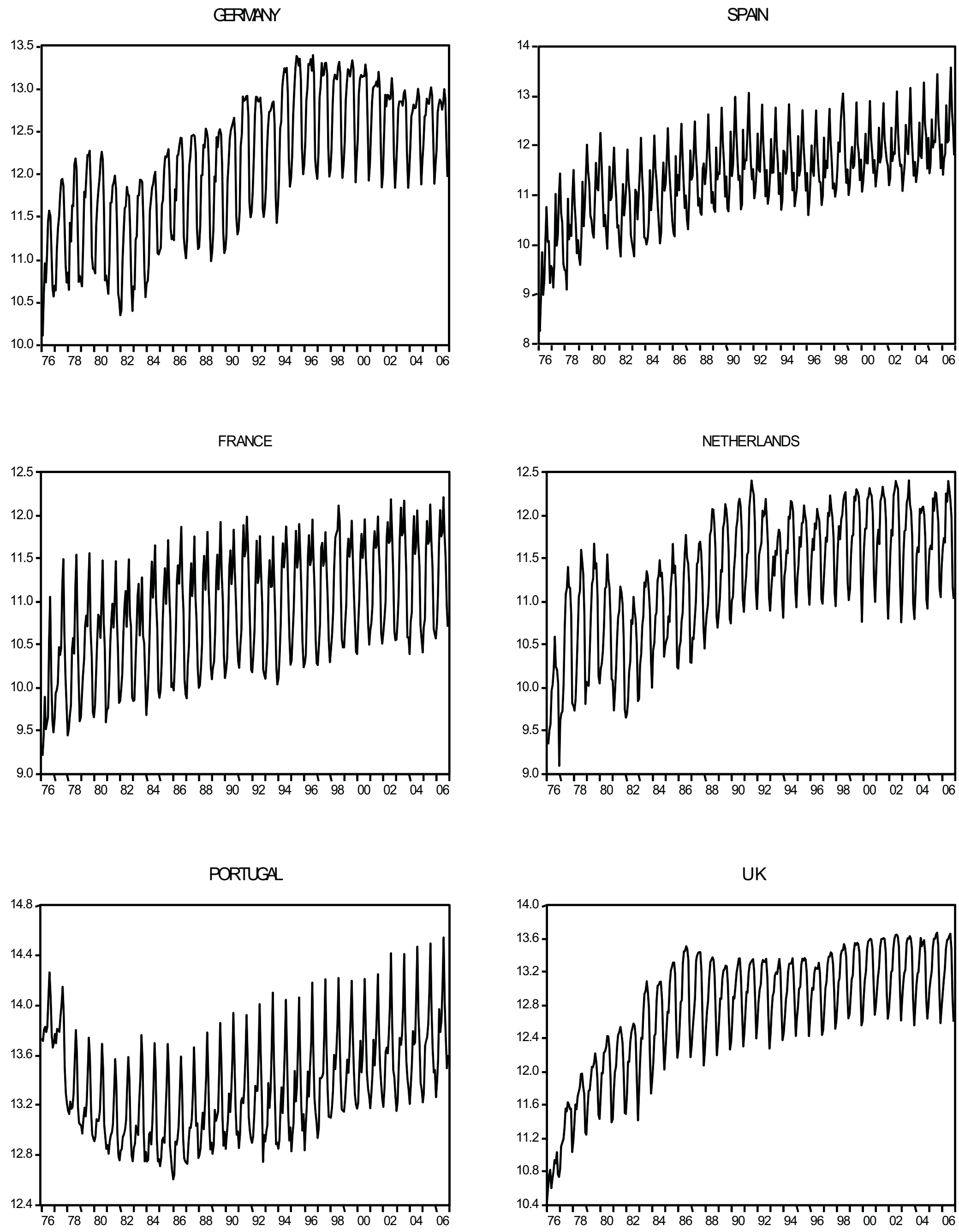



**Sources:** *Direcção Geral do Turismo* and *INE*.

Kingdom, and a *leptokurtic* distribution (distribution presents a greater concentration of observations around the mean than the normal) in the case of Spain and Portugal. The Jarque-Bera statistic (a measure of deviations from normality which is calculated considering the skewness and kurtosis of the series) suggests rejection of the null hypothesis that the series are normally distributed.

## Chart 2

LOGARITHMS OF TOURISM DEMAND OF THE MAIN SOURCE COUNTRIES
Logarithms




**Sources:** *Direcção Geral do Turismo* and *INE*.

To highlight the importance of seasonality, in Table 2 seasonal indices are presented according to the country of origin. These indices measure the degree of seasonal variation in the series.

**Table 1**

| DESCRIPTIVE STATISTICS OF THE REPRESENTATIVE SERIES OF TOURISM DEMAND IN PORTUGAL<br>Units: number of overnight stays | | | | | | |
|---|---|---|---|---|---|---|
| **Statistic/Country** | **Germany** | **Spain** | **France** | **Netherland** | **Portugal** | **UK** |
| **Mean** | 233047 | 106282 | 62340 | 94005 | 639348 | 390246 |
| **Median** | 173912 | 87492 | 49050 | 78663 | 554839 | 376851 |
| **Maximum** | 664129 | 483759 | 196305 | 243869 | 1824096 | 851087 |
| **Minimum** | 24715 | 3876 | 9998 | 8980 | 298841 | 34218 |
| **Standard deviation** | 172031 | 86365 | 39025 | 58138 | 268700 | 215659 |
| **Asymmetry** | 0.8569 | 1.8481 | 0.8279 | 0.6446 | 1.4047 | 0.1890 |
| **Flattening** | 2.5344 | 7.0391 | 2.8867 | 2.4320 | 5.0437 | 1.9442 |
| **Jarque-Bera** | 42.5813 | 404.6841 | 37.1872 | 26.7939 | 162.9393 | 16.9765 |
| **Prob (J-B)** | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0002) |

**Source:** Authors' calculations.

As shown in Table 2 it is in the summer months (particularly July and August) that the indices are higher. It should be noted that some countries also report high values in other months of the year (see for instance the months that coincide with the Easter holidays, *i.e.*, March and April, for Spain). The winter months (particularly December and January) are those that, in general, have lower indices (again Spain is an exception showing lower values in January and February).

In addition to seasonality, the series under analysis have volatility patterns as shown in Chart 3. To analyse volatility we used the squared residuals, $\hat{\varepsilon}_t^2$, of the following regression,

$$\Delta \log T_t = ARMA(1,1) + \sum_{i=1}^{12} \varphi_i D_{it} + \varepsilon_t \tag{6}$$

where $T_t$ is tourism demand from the countries under analysis, $D_{it}$, *i*=1,…,12, corresponds to a sea-

**Table 2**

| SEASONAL INDICES OF THE REPRESENTATIVE SERIES OF TOURISM DEMAND IN PORTUGAL | | | | | | |
|---|---|---|---|---|---|---|
| **Month/Country** | **Germany** | **Spain** | **France** | **Netherland** | **Portugal** | **UK** |
| **January** | 0.483 | 0.445 | 0.479 | 0.595 | 0.723 | 0.594 |
| **February** | 0.558 | 0.450 | 0.596 | 0.707 | 0.759 | 0.747 |
| **March** | 0.942 | **1.020** | 0.811 | 0.898 | 0.906 | 0.932 |
| **April** | **1.144** | **1.422** | **1.430** | 0.957 | **1.014** | 0.955 |
| **May** | **1.435** | 0.888 | **1.759** | **1.413** | 0.937 | **1.228** |
| **June** | **1.507** | 0.972 | **1.298** | **1.463** | **1.071** | **1.368** |
| **July** | **1.663** | **1.752** | **1.668** | **1.842** | **1.377** | **1.371** |
| **August** | **1.706** | **3.189** | **2.479** | **1.651** | **1.926** | **1.441** |
| **September** | **1.709** | **1.587** | **1.391** | **1.524** | **1.382** | **1.426** |
| **October** | **1.256** | **1.068** | 0.955 | **1.124** | 0.923 | **1.226** |
| **November** | 0.579 | 0.603 | 0.536 | 0.537 | 0.769 | 0.813 |
| **December** | 0.452 | 0.697 | 0.448 | 0.478 | 0.758 | 0.537 |

**Source:** Authors' calculations.
**Note:** To obtain these indices, moving averages for each month were first calculated – using the multiplicative method. These figures isolate the cyclical and seasonal components of the series. The seasonal indices result from the division of the original series by the moving averages, resulting in 12 indices. When this index exceeds the value of one this indicates that tourism demand exceeds the monthly components of trend and cycle which is an indication of the presence of seasonality.

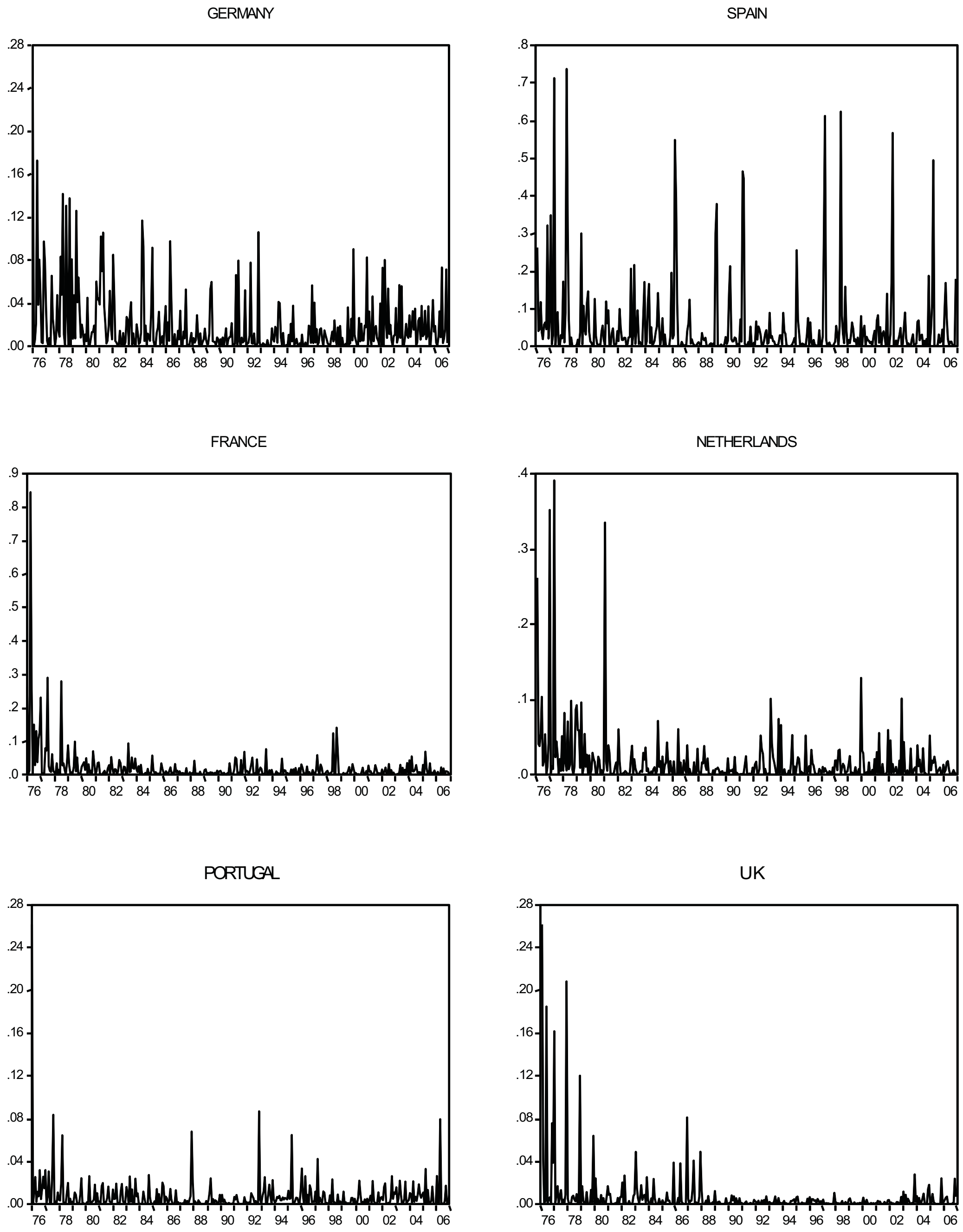
sonal dummy that is equal to 1 in month *i* and 0 otherwise, and ARMA (1,1) refers to a component of this type that was estimated for each series.

As shown in Chart 3, Portugal and the UK have the lowest levels of volatility and Germany and Spain, the highest levels. The Netherlands, France and the United Kingdom, in the early years display high

### Chart 3

VOLATILITY OF TOURISM DEMAND OF THE MAIN SOURCE COUNTRIES

Volatility




**Source:** Authors' calculations.

volatility, however it declines from 1980 onwards. These results were confirmed using the test for ARCH effects proposed by Engle (1982), based on which we found significant results for Germany, Spain and France and weak evidence for the Netherlands, Portugal and the United Kingdom. These results suggest that tourism demand from these latter countries appears to be more resistant to unanticipated shocks. A possible explanation for this phenomenon is related to the fact that the 80's correspond to the affirmation of this sector. Although tourism started to gain importance in the 60's, it is in fact only in the 80's that this industry consolidates its activity, particularly in these markets.

## 4. MODELLING SEASONALITY AND VOLATILITY OF TOURISM DEMAND IN PORTUGAL

For modelling purposes, the first differences of the logarithms of the series were considered. The graphs of the series are presented in Chart 4 and all appear to be stationary. Stationarity of these series was also confirmed using formal unit root tests (see Appendix).

### 4.1. Results

Given the importance of achieving an appropriate model for the conditional mean, several ARMA models have been tested to determine the most appropriate one to obtain estimates of the parameters of the mean equation. Table 3 presents the results for the mean equation for each country considering a GARCH(1,1)[2] as the model for volatility and Table 6 the results for the variance equations for the countries under analysis.

Table 4 presents the results for the conditional mean of the first differences of logarithms of tourism demand in Portugal. All estimates of the ARMA(1,1) parameters are significant for all countries. The results for the AR(1) model, are higher for the Netherlands and the United Kingdom, although for the latter they show an opposing sign compared to all other countries. The MA(1) estimates are also high for all countries, particularly in the case of France, the Netherlands and the United Kingdom, although once again for the latter they present a different sign. From the mean equations we also conclude that seasonality is indeed one of the main characteristics of tourism.

With regard to volatility, with the exception of Spain and the Netherlands, the GARCH (1,1) model seems to be the most appropriate. Estimates of conditional volatility suggest generally that there is no asymmetry, so that positive and negative shocks have similar effects on the volatility of the series of tourism under analysis.

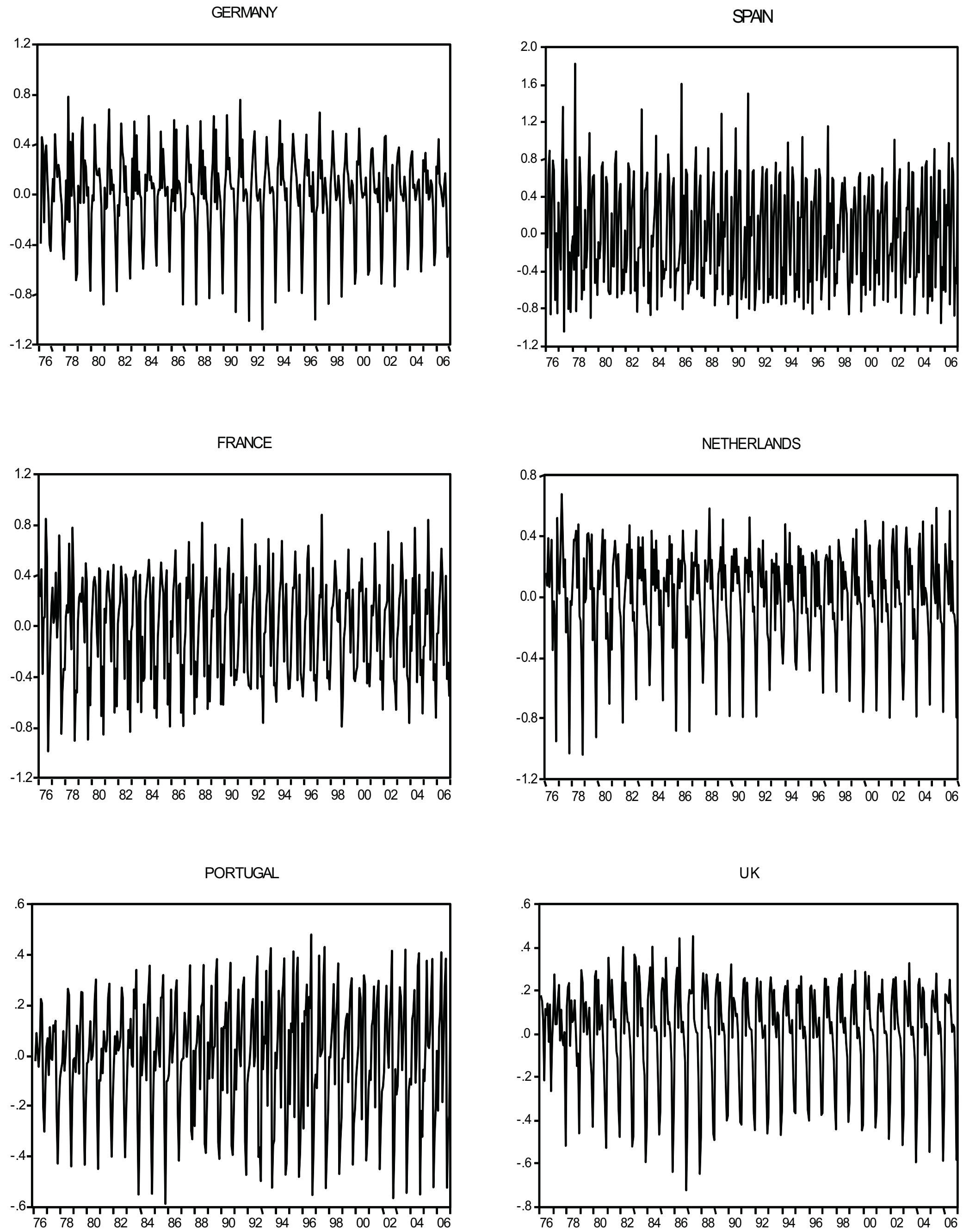
With respect to the GARCH(1,1) model, in the case of Germany, all parameters are significant and positive and the sum of α and $\beta$ is less than one, satisfying in this way the conditions required to ensure that $\sigma^2_t$ is positive and the stationarity of the model (*i.e.* existence of finite unconditional variance). The persistence of the shock in the long run is 0.983, very close to one, meaning that an unanticipated shock will have a strong impact on tourism demand of these tourists to Portugal and will

(2) The parameter estimates using an EGARCH or a TGARCH are qualitatively similar to those presented in Table 3 and are therefore omitted.

**Chart 4**

FIRST DIFFERENCES OF THE LOGARITHMS OF TOURISM DEMAND OF THE MAIN SOURCE COUNTRIES

First Differences of the Logarithms




**Source:** Authors' calculations.

persist for a considerable period of time. The same conclusion can be reached in the case of France and the United Kingdom. For Germany and for the United Kingdom, α is not significant (*i.e.* shocks have little impact in the short-run).

The EGARCH(1,1) model, when compared to the GARCH and TARCH models, is the one that best

## Table 3

**CONDITIONAL MEAN OF FIRST DIFFERENCES OF LOGARITHMS OF TOURISM DEMAND IN PORTUGAL - GARCH(1,1) MODEL**

| | | | Dependent | Variable | Δ LogT | |
|---|---|---|---|---|---|---|
| **Country** | **Germany** | **Spain** | **France** | **Netherland** | **Portugal** | **UK** |
| **Parameters** | | | | | | |
| AR[(a)] | 0.5490*** | | 0.3909*** | 0.6454*** | | -0.9592*** |
| | (0.0803) | | (0.0823) | (0.0483) | | (0.0511) |
| MA[(a)] | -0.8637*** | -0.7586*** | -0.8980*** | -0.8917*** | -0.5444*** | 0.9340*** |
| | (0.0436) | (0.0391) | (0.0333) | (0.0337) | (0.0641) | (0.0607) |
| January | 0.1019*** | -0.4383*** | - | 0.2808*** | -0.0430** | 0.1392*** |
| | (0.0289) | (0.0566) | | (0.0197) | (0.0168) | (0.0092) |
| February | 0.2099*** | | 0.2225*** | 0.2199*** | | 0.2235*** |
| | (0.0279) | - | (0.0287) | (0.0173) | - | (0.0149) |
| March | 0.5190*** | 0.7405*** | 0.3101*** | 0.2285*** | 0.2139*** | 0.2152*** |
| | (0.0278) | (0.0426) | (0.0225) | (0.0249) | (0.0172) | (0.0111) |
| April | 0.1841*** | 0.5113*** | 0.6489*** | - | 0.1217*** | 0.0472*** |
| | (0.0215) | (0.0386) | (0.0265) | | (0.0144) | (0.0136) |
| May | 0.2378*** | -0.5043*** | 0.2489*** | 0.4205*** | -0.0757*** | 0.2635*** |
| | (0.0195) | (0.0612) | (0.0278) | (0.0192) | (0.0292) | (0.0112) |
| June | - | - | -0.3132*** | - | 0.1244*** | 0.0997*** |
| | | | (0.0228) | 0.2038*** | (0.0328) | (0.0149) |
| July | 0.0709*** | 0.6565*** | 0.1531*** | (0.0236) | 0.2599*** | - |
| | (0.0236) | (0.0932) | (0.0232) | -0.0755*** | (0.0324) | - |
| August | - | 0.6177*** | 0.3869*** | (0.0212) | 0.3426*** | - |
| | | (0.1184) | (0.0322) | -0.0802** | (0.0211) | |
| September | - | -0.7256*** | -0.4771*** | (0.0323) | -0.3662*** | |
| | | (0.1109) | (0.048) | -0.2887*** | (0.0170) | |
| October | -0.2260*** | -0.3837*** | -0.3560*** | (0.0332) | -0.3883*** | -0.1551*** |
| | (0.0286) | (0.0853) | (0.0343) | -0.7179*** | (0.0290) | (0.0152) |
| November | -0.7736*** | -0.5547*** | -0.6026*** | (0.0204) | -0.1941*** | -0.4601*** |
| | (0.0214) | (0.0824) | (0.0234) | -0.1475*** | (0.0201) | (0.0071) |
| December | -0.2796*** | 0.1941*** | -0.1841*** | (0.0202) | | -0.3839*** |
| | (0.0247) | (0.0632) | (0.0253) | | | (0.0113) |

**Source:** Authors' calculations.
**Notes:** (a) The results in brackets correspond to Bollerslev and Wooldridge(1992) type robust standard errors.** and *** indicates statistical significance at 5% and 1%, respectively. – indicates that the variable is not statistically significant.

fits the volatility of Spain and the Netherlands. However, also for these countries there is no evidence of asymmetric effects (*i.e.* the hypothesis that $\gamma = 0$ is not rejected). The persistence of shocks measured through $\beta$, is significant for both countries and is strong in the case of the Netherlands and small in the case of Spain (0.9911 and 0.2193, respectively).

**Table 4**

CONDITIONAL VARIANCE OF FIRST DIFFERENCES OF LOGARITHMS OF TOURISM DEMAND IN PORTUGAL

| | | | Dependent | Variable | $\Delta$ LogT | |
|---|---|---|---|---|---|---|
| **Country** | **Germany** | **Spain** | **France** | **Netherland** | **Portugal** | **UK** |
| **Model** | **GARCH (1,1)** | **EGARCH (1,1)** | **GARCH (1,1)** | **EGARCH (1,1)** | **GARCH (1,1)** | **GARCH (1,1)** |
| **Parameters** | | | | | | |
| ω | 0.0002* | 3.2269*** | 0.0006*** | -0.0338 | 0.0044 | 0.00005*** |
| | (0.0001) | (0.3148) | (0.0002) | (0.0455) | (0.0037) | (0.00001) |
| GARCH α | 0.0195 | - | 0.0471** | - | 0.1078 | 0.0104 |
| | (0.0162) | | (0.0203) | | (0.0673) | (0.0099) |
| GARCH β | 0.9635*** | | 0.8974*** | | 0.3844 | 0.9668*** |
| | (0.0190) | | (0.0210) | | (0.4487) | (0.0096) |
| EGARCH α | | 0.9813*** | | -0.0136 | | |
| | | (0.1139) | | (0.0324) | | |
| EGARCH β | - | 0.2193** | | 0.9911*** | - | - |
| | - | (0.0985) | | (0.0051) | - | - |
| EGARCH γ | - | 0.1309 | | -0.0071 | - | - |
| | | (0.0836) | | (0.0189) | | |
| Log-Likelihood | 229.3550 | 69.3288 | 271.2198 | 235.3283 | 389.2318 | 475.2967 |
| AIC | -1.1641 | -0.2928 | -1.3796 | -1.3623 | -2.0228 | -2.4935 |
| BIC | -1.0160 | -0.1345 | -1.2103 | -1.1747 | -1.8750 | -2.3454 |

**Source:** Authors' calculations.
**Notes:** The results in brackets correspond to Bollerslev and Wooldridge(1992) type robust standard errors. ** and *** indicates statistical significance at 5% and 1%, respectively.

## 6. CONCLUSION

From the analysis of this study, it is possible to observe that seasonality is indeed one of the main characteristics of tourism. The parameter estimates for the winter months are negative and positive for the warmer months. Furthermore, the results for the conditional mean of the first differences of logarithms of tourism demand in Portugal show that all estimates of the ARMA(1,1) parameters are significant for the three models and for all countries.

The results suggest that in general the GARCH (1,1) model provides an appropriate measure of conditional volatility of most of the series considered. Based on this model, it was noted that for Germany, the persistence of the shocks in the long-run is 0.983, very close to one, meaning that an unanticipated shock will have a strong impact on tourism demand of these tourists to Portugal and will perdure for a considerable period of time. The same conclusion can be reached in the case of France and the United Kingdom. However, for Germany and for the United Kingdom, α is not significant suggesting that shocks may have only a long-run impact). For domestic demand evidence of volatility is very low suggesting some resistance to demand shocks.

Since tourism is a relevant economic activity, it is important to note that an unanticipated shock, will have implications on tourism demand for Portugal. In addition to the economic impacts on employment and investment within the sector, other activities directly related to tourism, such as, for example, construction, agriculture, etc., will also be affected. On the other hand, it is necessary to ascertain the extent to which a shock, may divert demand to other countries that offer the same type of products. Since Germany, Spain, France, the Netherlands, Portugal and the United Kingdom are the main source countries of tourists, it becomes increasingly necessary to improve competitiveness, develop new products, new centres of attraction, and new markets, as well as, look to the needs of qualified services and human resources. These and other measures are relevant for the industry to remain an important sector of the economy.

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## APPENDIX

The ADF unit root test was applied to these series to test for the presence of unit roots. Test regressions with 12 seasonal dummies only and with 12 seasonal dummies and a time trend were considered, i.e.,

$$\Delta X_t = \gamma X_{t-1} + \sum_{i=1}^{12} \varphi_i D_{it} + \sum_{i=2}^{p} \beta_i \Delta X_{t-i-1} + \varepsilon_t \quad (7)$$

$$\Delta X_t = \gamma X_{t-1} + \phi t + \sum_{i=1}^{12} \varphi_i D_{it} + \sum_{i=2}^{p} \beta_i \Delta X_{t-i-1} + \varepsilon_t \quad (8)$$

The critical values for 372 observations were obtained by Monte Carlo simulation in *GAUSS 9.0* and the results for 1%, 2,5%, 5% and 10% significance levels are presented in Table A1.

### Table A1

CRITICAL VALUES FOR DICKEY AND FULLER (1979) TEST WITH 12 SEASONAL DUMMIES AND WITH 12 SEASONAL DUMMIES AND A TIME TREND FOR 372 OBSERVATIONS

| Deterministic Elements | Percentiles | Value |
|---|---|---|
| **12 Seasonal Dummies** | 0.010 | -3.381 |
| | 0.025 | -3.090 |
| | 0.050 | -2.806 |
| | 0.100 | -2.508 |
| **12 Seasonal Dummies and Trend** | 0.010 | -3.864 |
| | 0.025 | -3.554 |
| | 0.050 | -3.320 |
| | 0.100 | -3.039 |

**Source:** Authors' calculations.

The results of the test are in Table A2.

These results and the graphical representation of the series (Chart 4), show that the first differences of the logarithms of the series are stationary.

### Table A2

RESULTS OF THE DICKEY AND FULLER (1979) UNIT ROOT TEST

| País/Variável | Variável Exógena | T | LogT | ∆LogT |
|---|---|---|---|---|
| Germany | Seasonal Dummies | -1.088 (13) | -1.143 (13) | -4.104 (12) *** |
| | Seasonal Dummies and Trend | -1.879 (13) | -2.334 (13) | - |
| Spain | Seasonal Dummies | -1.374 (13) | -2.881 (12) | -6.101 (12) *** |
| | Seasonal Dummies and Trend | -2.960 (13) | -3.215 (12)* | - |
| France | Seasonal Dummies | -1.361 (13) | -1.621 (12) | -6.284 (12) *** |
| | Seasonal Dummies and Trend | -4.617 (13) *** | -3.451(12) ** | - |
| Nethelands | Seasonal Dummies | -1.223 (12) | -2.245 (13) | -4.766 (12) *** |
| | Seasonal Dummies and Trend | -2.612 (12) | -3.140 (13) * | - |
| Portugal | Seasonal Dummies | -2.931 (13) ** | -2.816 (14) ** | -3.953 (13) *** |
| | Seasonal Dummies and Trend | -5.018 (13) *** | -5.535 (14) *** | - |
| UK | Seasonal Dummies | -1.686 (12) | -4.108 (12) *** | -4.479 (12) *** |
| | Seasonal Dummies and Trend | -1.713 (12) | -3.503 (13) ** | - |

**Source:** Authors' calculations.