Volatility in City Tourism Demand

Alexandra Sofia Marinho da Silva Mendes

Thesis specially presented for the fulfilment of the Degree of

Doctor in Tourism Management

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Author's Declaration of Originality

I hereby certify that I am the sole author of this thesis and that, to the best of my knowledge, my proposal does not infringe upon anyone's copyright nor violate any proprietary rights.

20/07/2018

To Adriana and Mariana

Acknowledgements

First of all, I am grateful to the two most important people in my life: my daughters, Adriana and Mariana, to whom I dedicate this work. For the days when I had no patience, for my tiredness and, above all, for inspiring me every day, with their happiness, their laughs, their music and their unconditional love.

To my Mother, to my Father, to my Sister and to my nephews, Artur and Martim, for always being there, for me and my daughters, for believing, for having always counted on you, at all moments of my life. Anyway, for teaching me the true meaning of the word Family.

To my Friends, those who shared anguishes and successes, those who always believed. Thank you for being part of my Family.

I also have to express my gratitude to my supervisors. Professor Ana Brochado, for having, since the beginning of this doctoral program, relied on my research ability, for guiding me on the best paths, for being a true guide, inspiring me in the research process, and making me believe that I would achieve my goals. Professor Rui Menezes, for his availability, for being able to transmit advanced theoretical contents in a simple and concrete way, inspiring me in the way I teach and for having super guided me methodologically in this research process. Thank you both with all my heart.

To Professor Antónia Correia for having believed and for her inspirational way of making research in Tourism. Thank you so very much.

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List of Abbreviations and Acronyms

ADF Augmented Dickey–Fuller

AIC Akaike's Information Criterion

ANN Artificial Neural Networks

ARCH Autoregressive Conditionally Heteroscedastic

ARDL Autoregressive Distributed Lag

BG Breusch–Godfrey

EGARCH Exponential Generalized Autoregressive Conditionally Heteroscedastic

GARCH Generalized Autoregressive Conditionally Heteroscedastic

GDP Gross Domestic Product

GJR Glosten-Jagannathan-Runkle

JESSICA Joint European Support for Sustainable Investment in City Areas

LM Lagrange Multiplier

OLS Ordinary Least Squares

PP Phillips-Perron

SARIMA Seasonal Autoregressive Integrated Moving Average

SJR SCImago Journal Rank

SNIP Source Normalized Impact per Paper

SSA Singular Spectrum Analysis

STSM Structural Time Series Model

TARCH Threshold Autoregressive Conditionally Heteroscedastic

TGARCH Threshold Generalized Autoregressive Conditionally Heteroscedastic

UEFA Union of European Football Associations

UK United Kingdom

UNESCO United Nations Educational, Scientific and Cultural Organization

UNWTO United Nations World Tourism Organization

VAR Vector Autoregressive

Abstract

The main objectives of this research are to identify, through a systematic literature review, the potential benefits of the use of volatility models in tourism, to study the volatility of tourism demand in cities and to compare models of volatility between different destinations and source markets. The three cities analysed in Portugal were Coimbra, Lisbon and Oporto and the source markets that were studied were the domestic market, the total overnight stays, Brazil, France, Germany, Italy, Spain, the United Kingdom and other non-specified countries.

The systematic review of the literature was carried out in order to identify, in a temporal perspective, the use of each methodology, variables used, data frequencies, temporal window, type of territories and geographic object of each study. The semantic analysis of the state of the art was also a methodology used. After a preliminary analysis of the time series, models that literature indicates as more suitable to estimate the volatility were used, namely, models of autoregressive conditional heteroscedasticity: ARCH, GARCH, EGARCH and TGARCH models.

The most suitable models for each source market, in each city, were identified, as well as the existence of asymmetries face to positive and negative shocks, their magnitude and their persistence. Different models of volatility were identified in each city for each source market, as well as, different types of persistence of volatility, in each market and city, and different magnitude in face of good news and bad news, which strengthens the need to adjust the modelling of tourism demand for each market and, within a country, at a more detailed territorial scale.

The use of volatility models is quite recent in tourism demand modelling and had not yet been applied in cities in Portugal, for which, despite the growing importance in terms of tourism, there are no studies of modelling focusing on the tourism demand.

Modelling tourism demand is essential when tourism policymakers plan tourism activities. The tourism industry may be extremely sensitive to specific events' effects, so good models must be found that reflect volatility that varies within each city and for each source market and policies must be adapted to each of the source/destination pairs.

Keywords: Volatility, City Tourism, Tourism Demand, Time Series Modelling

1. Introduction

1.1. Background and Motivations

According to the United Nations World Tourism Organization (UNWTO, 2018b), international tourists numbered 1323 million in 2017, generating 10% of the world's Gross Domestic Product (GDP) and creating one out of every 10 jobs worldwide. In 2017, international tourism grew by 8% in Europe, which stayed in first place in terms of international tourist arrivals with thereabout 678 million visitors. This can also be seen, as the evolution of international tourist arrivals, in Table 1, in millions, shows that in the last 15 years, total world international tourist arrivals almost doubled (81% growth) and the global growth rate in Europe was of 60%.

Table 1 - International tourist arrivals by region (in millions) 2001-2016

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
World	684	703	694	764	809	847	901	919	882	953	994	1040	1094	1139	1191	1239
Europe	388	397	407	424	453	462	485	487	462	489	521	541	566	576	604	619
Asia and the Pacific	121	131	113	144	154	155	182	184	181	208	218	234	254	270	284	306
Americas	122	117	113	126	133	167	144	148	141	150	156	163	168	182	193	201
Africa	29	30	31	34	35	41	43	44	46	50	50	52	55	55	53	58
Middle East	24	28	30	36	34	41	47	56	53	55	50	51	51	56	57	56

Source: adapted from UNWTO (2005, 2006, 2008, 2010, 2016, 2017, 2018c)

A perishable product such as tourism should be the subject of appropriate planning. Modelling through forecasting models allows anticipating the future, by providing those who are responsible for tourism policies an essential tool in the management (Archer, 1987; Witt & Witt, 1995).

Research on tourism demand in Europe seems to be of great importance since that, between 2008 and 2017, the growth rate of the overnight stays rose from 1.3% to 8% (UNWTO, 2018a). Despite this importance, few studies have been conducted on this topic, on the city level, which, according to Mazanec and Wöber (2009) and Bauernfeind, Önder, Aubke and Wöber (2010), is, mainly, due to the lack of availability of data, as well as the hard comparability.

For Taleb Rifal, secretary-general of UNWTO (2012), cities are vibrant epicentres of culture and commerce as, nowadays, half of the world´s population lives in cities and it is expected that by 2030, five billion people will be urbanized. Cities, being some of the world's greatest tourism destinations, attract a growing number of visitors every year, generating a positive impact on the local economy by creating jobs, stimulating foreign exchange and promoting investment in infrastructure that benefits residents and visitors.

According to the UNWTO (2018b), in 2017, the number of international tourists (overnight stays) growth 7% face to 2016, an increase for the eighth consecutive year, above the forecasting average and five out of the Top10 destinations in the world are in European Union (UNWTO, 2018a).

One of the international trends that pretends to impact tourism is an increasing number of megacities (Turismo de Portugal, 2017). Tourism demand modelling is very dependent on the availability of data and on the possibility of comparability. Furthermore, official data are often available for large regions within a country, without being disaggregated by source markets, often annual and about a year lag to the current date. Examining the degree of persistence of good and bad news, disaggregating data by nationality, is a line of research proposed by Gil-Alana and Huijbens (2018) when they recently studied tourism demand in Iceland.

Given the notable lack of literature on tourism demand in cities in Portugal and taking into account the growing importance of urban tourism worldwide, particularly in Europe, this research intended to fill this gap, in the scientific literature on tourism, by providing, to those responsible for the management and planning of city tourism, a tool that allows to adapt the policies of each city, relative to each source market, and to those who study about tourism demand modelling, a recent framework of methods that could enhance this research area.

According to Balli and Tsui (2015), modelling the volatility of tourism demand is imperative, particularly for policy makers, once governments and tourism authorities or organizations should be certain about the volatility of tourism demand.

Modelling volatility is characteristic of the research in the financial markets, where negative shocks make volatility more persistent. In the area of tourism demand, modelling of volatility shows different types of persistence and magnitude in the face of increases or decreases, depending on the different source markets, and can also improve forecasting models, which are fundamental in the planning and management of any tourism destination.

1.2. Objectives

The first objective of this research is to offer a systematic literature review, which allows proving the emerging need to use volatility models, mainly used with financial data, in the modelling of tourism demand, as well as the most appropriate variables, data frequencies, temporal window and, above all, the most appropriate methodologies to reach good models.

To study tourism demand modelling in cities is the second major objective of this research. This analysis will be made through tourism demand volatility modelling. Modelling of tourism demand volatility will be based on overnight stays data from the main markets.

Finally, the last objective of this research is to compare the volatility of tourism demand between different cities for the same source market and between source markets within each city.

The ambition of this research thesis is to answer the following research questions:

> Q1) Is volatility an emergent theme in tourism demand modelling?
>
> Q2) Are there differences between the persistence of tourism demand volatility, in a specific city tourism destination, for different source markets or between different city tourism destinations, for a specific source market?
>
> Q3) Are there differences between the persistence of tourism demand volatility for good and bad news in a specific city tourism destination for the different source markets or between different city tourism destinations, for a specific source market?
>
> Q4) When there are differences in tourism demand volatility persistence, are there differences in the magnitude of the good news and bad news, in a specific city tourism destination, for different source markets or in different cities, for a specific source market?

The expected outcomes from this research are, essentially, to achieve accurate models, which allow an excellent analysis of the volatility which, consequentially, leads to a good planning of the tourism resource 'city' within each region and, also, enables adapting actions to each inbound market.

It is expected that this research contributes to the literature by enhancing the empirical evidence of phenomena previously studied in different tourism regions of the world, particularly in cities.

This research can open avenues for future research that may improve planning of tourism, taking into account 'ups' and 'downs' in tourism demand, as well as the persistence of volatility. Such planning can be improved to each of the source markets and might allow medium-term measures to counteract declines in demand.

1.3. Thesis Overview

This thesis is organized in five chapters, references and an appendix section: introduction, literature review, methodology, results and discussion, and conclusions.

The introduction chapter briefly describes the background and motivations, objectives and research questions. The structure of the thesis presented, also.

The second chapter provides a thorough review of city tourism demand and a detailed review on tourism forecasting models research that includes a systematic literature review of tourism forecasting studies that previously mentioned volatility. This literature review identified the most appropriate methodologies for analysing the tourism demand volatility as well as new features in this area and current research lines.

The third chapter starts with the research paradigm and the conceptual framework of this study. Then, the research context was introduced, followed with a description of the database used. A discussion on the methods applied in the empirical work was presented in this section.

The fourth chapter covers a preliminary data analysis and the empirical results for the estimated models for overnight stays' returns in Coimbra, Lisbon and Oporto, from Portugal, Brazil, France, Germany, Italy, Spain and the United Kingdom (UK). Other unspecified countries were also analysed (in a category identified by Others) and, also, the total of overnight stays in each of the three cities. An analysis of each model for the three cities, for each source markets, also was presented in this chapter, as well as a global evaluation.

The last section presents a summary of the results, theoretical and managerial implications and avenues for future research.

2. Literature Review

This chapter presents the importance of tourism in cities demonstrated in the scientific literature, in the World, in Europe and, particularly, in Portugal. Then, it summarizes the historical importance of the analysis of tourism demand, the various models that have been used in the tourism demand modelling and the types of studies, like comparative studies of different methodologies that were also analysed, since the beginning of scientific studies in this research area.

At last, based on a quantitative and semantic analysis of more recent studies, a systematic in-depth literature review of tourism demand modelling methods used in tourism research during the last five years was conducted. This systematic review of the literature also intends to offer an alternative classification of the methods applied in modelling tourism demand. The identification of variables, appropriate models, data and time window for tourism demand analyses was also a goal of this chapter, as well as the understanding of the rationales for using volatility models when modelling tourism demand.

2.1. City Tourism

The International Recommendations for Tourism Statistics (United Nations Department of Economic and Social Affairs, 2017), states that a tourism product represents a combination of different aspects, like characteristics of the places visited, modes of transport, types of accommodation, specific activities at the destination, among others, around a specific core of interest, like visits to historical and cultural sites or to a particular city. This concept of product is not related to the one used in economic statistics and is used by professionals in the tourism. As a marketing tool, stakeholders use a classification of tourism products that includes the tourism product ‘city tourism’.

According to the same document, the observation of the flows of domestic tourism requires the use of different statistical procedures because there are no international borders to cross. Therefore, accommodation statistics, like overnight stays, are an important statistical source of information on domestic visitors. This kind of statistics are based on a statistical operation covering establishments providing paid accommodation, so the part of overnight travel which is attributed to unpaid accommodation, like overnight stays with friends and relatives or trips to owner-occupied vacation homes, is excluded. Therefore, travel by non-residents to a country or within a country are called inbound or domestic tourism, respectively. For inbound tourism, it is essential to classify all overnight stays by country of residence rather than by nationality because it is in the country of residence where the decisions are taken and implemented regarding the organization of the trip.

With regard to city tourism, Shaw and Williams (2002) believe that the main motivations are business tourism and conferences, but, also, knowledge of city history and culture. In some cities, there has been a process of urban renewal, which has led to development of tourism, as in Barcelona, where there was a great transformation of the spaces for the Olympic Games in 1992. The creation of slogans, such as, ‘I Love New York’ or ‘Bogotá, 2600 meters closer to the stars’ have attracted visitors and contributed to cities revitalization. These authors mentioned the importance of tourism industry as a reinforcement of global cities, like London, New York and Paris.

According to Mazanec and Wöber (2009) the role of the analysis of a comprehensive data base of European city tourism statistics is making an effort to provide convincing information and perform forecasts, as an evidence of the information gain in this tourism product. The authors showed that cities are destinations resistant to seasonality effects and developed work to examine city tourism demand in their own environment of study and management.

Cities are considered, by Minghetti and Montaguti (2010), places in motion and nodes of dynamic networks of different physical and virtual instabilities, like tourists, residents, businesses, capitals, investments, culture and knowledge, that, continuously, redesign the urban space. These authors studied the organization of tourism practices, city image and brand effectiveness of eleven European cities, namely: Barcelona, Bruges, Florence, Istanbul, London, Paris, Prague, Rome, Seville, Venice and Vienna having categorized them in four clusters: one with four major cities (Barcelona, London, Paris and Rome), the second with three traditional art cities (Venice, Florence and Bruges), the next with only one city (Vienna) and the last one included three emerging city tourism destinations (Istanbul, Prague and Seville).

Ellero and Pellegrini (2014) verified some forecasting models in the United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage City of Milan, Italia, using accommodation data from medium-size hotels situated in this city tourism destination, where fairs and special events, like big concerts or expositions, are rather frequent. They identified holiday, leisure and recreation travellers booking with tour operators or individually, visiting the city in days in which both cultural and religious events take place, and business and professional travellers, booking as corporate or single, visiting a fair during a weekend.

Falk and Vieru (2016b) have made some research about the sensitivity to the exchange rate between the two countries' currencies of Russian tourism demand in 37 Finland cities with data based on overnight hotel stays at a monthly level for the period from January 1999 to July 2015 and they have found that it is highest in neighbouring cities close to the border.

All participating cities, including Lisbon, in the 'Cities 2012 Project' promoted by the UNWTO Affiliate Members Programme declared that tourism is a key resource for cities. Moreover, they concluded that the future development of cities would demand policies that take into account cities' stability, offering, at the same time, the best experience for visitors. The diverse and flexible products of the city are vital for tourism and urban tourism can trigger a more competitive approach in promoting destinations, stimulating innovation and implementing a consistent brand image (UNWTO, 2012). Urban tourism can contribute for revenue generation, for innovative practices in heritage conservation and management, and for creating public consciousness of culture and cultural heritage (UNWTO, 2018b).

The prospective diagnosis given by Turismo de Portugal (2015) indicated a higher forthcoming frequency of city breaks as a tourism sociocultural trend that will lead to the development of events in low season.

Guedes and Jímenez (2015) derived four cluster based on all classified cultural attractions. Cluster one consists of the city of Lisbon, cluster two comprises Oporto city and cluster three includes Coimbra, Évora and Sintra. These authors concluded that organized tourism programs based on cultural heritage reduce the asymmetry of the spatiality of Portuguese tourism model and that there seems to be a close spatial relation between cultural attractions concentration, mainly classified cultural heritage, and tourism.

European Commission developed, in co-operation with the European Investment Bank and the Council of Europe Development Bank an initiative entitled Joint European Support for

Sustainable Investment in City Areas (JESSICA) that supports sustainable urban development and regeneration of cities through financial engineering mechanisms (Urbact, 2018).

Coimbra was englobed in CityLogo European network that was a global learning experience on city branding and city marketing in modern urban politics for a better positioning of cities in the economic field. Presently this city is part of the Gen-Y City, a project that includes activities dedicated to diagnosis and support for new and creative businesses, as a means of refreshing city centres (Urbact, 2018).

A method for estimating the bike-sharing demand was applied in the city of Coimbra to help in decision-making for transportation planners, policymakers and investors and may, in the future, include the consideration of other characteristics, such as tourism attractions and parks or recreation areas. It should be also considered the demand associated to public transport, to understand which public transport mode bike-sharing users chose to complete their trip. Therefore, several information was also collected in socio-economic variables for each district and each traffic zone that are part of this case study, in order to have a detailed demand determination framework (Frade & Ribeiro, 2014).

Lisbon is part of the network Interactive Cities, a pioneer project directed to improve urban management in European cities through the use of digital, social media and user generated content (Urbact, 2018). The tourism experience in Lisbon has been analysed by means of a questionnaire administered to tourists who had visited Lisbon, allowing the determination of the influence of demographic and travel behaviour characteristics on destination attributes (Sarra, Di Zio, & Cappucci, 2015).

Oporto was part of three European networks: JESSICA 4 Cities, CSI Europe and ENTER.HUB. The aim of JESSICA 4 Cities was to develop a 'JESSICA Toolbox for Cities' that would enable an effectively use of JESSICA's opportunities after a review of local problems. The purpose of CSI Europe was helping the development and implementation of financial instruments. ENTER.HUB promoted the role of railway interfaces of regional relevance in medium cities, as instruments for urban development and economic, social and cultural regeneration. Currently Oporto is englobed in three other European networks: In Focus, 2nd Chance and SmartImpact. In Focus pretends to improve cities competitiveness and job creation capability by positioning in the new economic scene. The aim of 2nd Chance is to activate unoccupied buildings for a sustainable urban development. Finally, SmartImpact intends to develop models for organizations to adapt their structures to smart cities and innovation ecosystems (Urbact, 2018).

According to Santos, Valença and Fernandes (2017) after the historic centre of Oporto being classified as a UNESCO World Heritage Site, in 1996, and given the specificities and constraints of this area, an organization, Porto Vivo, was created in November 2004, with the objective of promoting Oporto's downtown and historic centre rehabilitation. The outcomes of this project, observed until now, have been encouraging the promotion and expansion of this city, in general.

2.2. Tourism Forecasting Models

Studying the characteristics of tourism from the economic perspective is an area of research established by Guthrie (1961), Gerakis (1965) and Gray (1966).

Tourism activities have become extremely important for economies, in particular for regions, representing a strategic sector of economic and social development. In this context, tourism research is indispensable for understanding and analysing underlying phenomena and aspects of regional differentiation that are the basis for international competitiveness of destinations (i.e. countries, regions or locations). The tourism development of a given territory throughout the various stages of the tourism life cycle needs to be directed and controlled by taking into consideration the particular conditions of this sector's activities and the relevant region's current situation (Butler, 1980).

Anticipating the future of tourism activities facilitates the development of better plans and appropriate policies. With this in mind, van Doorn (1982) was the first to conduct an analysis that included planning, policymaking and forecasting, as well as measuring the utility of these for individuals responsible for tourism plans and policies.

Considering the vast consequences of various crises and disasters, events' impact evaluation has attracted much interest in tourism demand forecasting research (Song & Li, 2008). For these authors it is crucial to develop some forecasting methods that can accommodate unexpected events in predicting the potential impacts of these on-off events through scenario analysis. Other areas that have still not been extensively researched include tourism cycle analysis, turning point and directional change forecasting. More attention has been paid on forecasting the level of tourism demand while limited research has been conducted on the accuracy of directional change or turning point forecasts. Considering the significant policy implications of these forecasts, additional studies still need to be conducted in this field of research.

The comparison of precision model accuracy has been widely analysed in the literature, in particular in tourism demand modelling. In this sense, it is important to perform a review of the existing literature related to tourism demand modelling, in a way that allows the identification of the most common variables in this type of study, the type of data that can be used and the best models. The advantages and disadvantages of different methods of forecasting and estimation of tourism demand have been analysed by different authors. The use of time series models provides concepts and techniques that facilitate the specification, the estimation and evaluation, often producing more accurate results than other more complex modelling techniques, based on the analysis performed by Choy (1984), Martin and Witt (1989) and R. J. C. Chen, Bloomfield and Cubbage (2008).

No single method could outperform others, on all occasions. Some common issues were identified in recent forecasting competition studies. Firstly, only a limited number of models were selected for forecasting competitions, and no clear justifications were given as to why these candidates instead of others were chosen (Song & Li, 2008). However, Coshall (2009) shows that univariate volatility models are proving to be important tools in the modelling of positive and negative shocks on tourism demand.

Athanasopoulos, Hyndman, Song and Wu (2011) presented a research based on a competition between different forecasting methods applied to tourism, having exclusively used variables related to tourism. They found supremacy of time series methods, clarifying that even in tests where causal models have proved best, certainly, the time series methods would also be good.

The piecewise linear model was constructed to forecast tourism demand for Macau by Chu (2011) and its forecasts were compared with Autoregressive, Seasonal Autoregressive Integrated Moving Average (SARIMA) and Fractionally Integrated Autoregressive Moving Average models. This author concluded that piecewise linear model is significantly more accurate than those models.

Song, Li, Witt and Athanasopoulos (2011) combined a Structural Time Series Model (STSM) with a time-varying parameter regression approach to develop a causal STSM to model and forecast tourist arrivals to Hong Kong from four source markets, comparing this model to other seven competitors, which proved to be much more accurate.

The present review focused on research published after the last major literature review, in which Song, Dwyer, Li and Cao (2012) analysed articles published until 2011. Thus, the current analysis reviewed papers published from 2012 to the present. Previous literature reviews have focused primarily on the methods used, so the present analysis sought to complement these reviews by providing a temporal perspective on the use of each method in modelling tourism demand, as well as the variables included. This review also aimed to identify the frequency of existing studies by territories and their geographical distribution. A hybrid methodology was used, including semantic and systematic quantitative analyses, which also distinguishes the present research from most previous literature reviews.

Song et al. (2012) argued that the particular characteristics of the tourism industry call for new perspectives and approaches, stating that demand analysis continued to dominate economic studies of tourism in articles published until 2011. Complementing the literature reviews performed by Song and Li (2008), Goh and Law (2011) and Song et al. (2012), the present review sought to identify the type of data used (i.e. daily, weekly, monthly, quarterly or annual data). It also focused on the time window, type of destination analysed (i.e. country, region, city or other) and methodology (i.e. studies that model tourism demand or its volatility or that make forecasts). Other aspects, concentrated on, in this review, were variables used in models, journals that have published articles on tourism demand modelling - based on CiteScore[1], SCImago Journal Rank (SJR)[2] and Source Normalized Impact per Paper (SNIP)[3] - and the authors that do research on this topic.

Thus, this study conducted a systematic review, which is a method of identifying and synthesizing all evidence of research of sufficiently good quality within a specific topic (Victor,

[1] This is the ratio between the number of citations a journal receives in one year to documents published in the previous three years and the number of documents indexed in Scopus published in the same three years.
[2] This is a prestige metric based on the idea that 'all citations are not created equal'. The subject field, quality and reputation of cited journals have a direct effect on the value of citations.
[3] SNIP measures contextual citations' impact by weighting citations based on the total number of citations in a subject field.

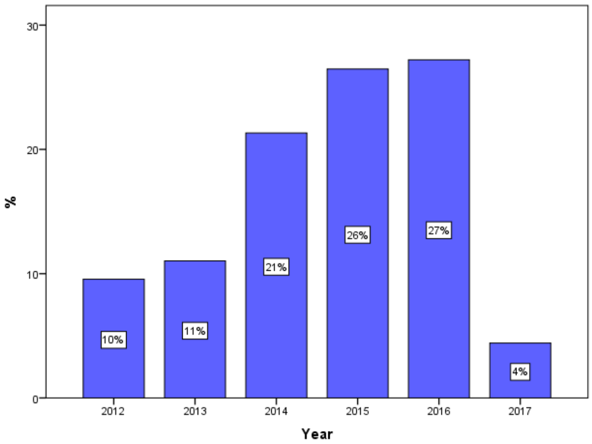
2008). The systematic analysis took into account 136 articles published in journals identified in a recent article by Gursoy and Sandstrom (2016), who summarized the top scoring tourism and hospitality journals based on combined scores, as well as those suggested by the aforementioned articles. The present search used the keywords ‘tourism demand AND volatility’ in all fields. The following data bases mainly used were ScienceDirect, Routledge Online, Taylor & Francis Online, Emerald Insight, Ingenta Connect, SAGE and RePEc – Research Papers in Economics.

All articles analysed were compiled on a worksheet in Microsoft© Excel (Microsoft© Office Professional Plus 2016, Version 16.0.4266.1001) file, including the studies’ title, authors, journal, date, abstract, keywords, time window, data frequency, model applied, variables used and regions considered. This worksheet was analysed using IBM© SPSS© Statistics (Version 24) and Leximancer© (Version 4.5) software.

Leximancer© (Version 4.5) is a data mining software that, through text analysis, visualizes texts’ concepts and themes, and uses a machine learning technique that is useful in literature reviews (Crofts & Bisman, 2010; Jin & Wang, 2015; Stechemesser & Guenther, 2012; Stockwell, Colomb, Smith, & Wiles, 2009). In the present study, abstracts were subjected to semantical analysis because these texts are lexically dense and focus on the articles’ main topics (Cretchley, Rooney, & Gallois, 2010).

The articles were published from 2012 to 2017, with a tendency toward a greater frequency of studies on tourism demand analysis in tourism research as shown by the number of studies doubling between 2013 and 2014 (Figure 1).

Figure 1 - Distribution of analysed articles by year of publication



Source: author

The distribution of journals with more than one publication on this topic, during the analysed years, is shown in Table 2, which reveals that the most prominent journals in the area of tourism demand analysis are *Tourism Management*, *Tourism Economics* and *Journal of Travel Research*.

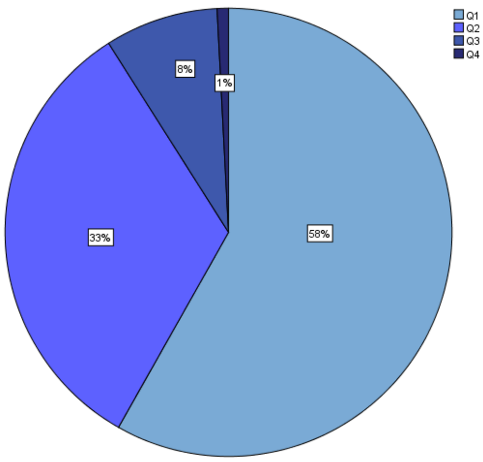
Table 2 - Distribution of the number of articles by scientific journals

Date	**Year**						**Total**
	2012	2013	2014	2015	2016	2017[ǂ]	
Annals of Tourism Research	0	3	0	1	4	0	8
Current Issues in Tourism	0	0	0	1	7	0	8
Economic Modelling	0	1	1	1	0	1	4
IMF Working Papers	0	0	2	0	0	0	2
International Journal of Contemporary Hospitality Management	0	0	1	1	0	0	2
International Journal of Tourism Research	1	1	2	3	0	1	8
Journal of Environmental Management and Tourism	0	0	1	1	1	0	3
Journal of Travel and Tourism Marketing	0	0	1	0	1	2	4
Journal of Travel Research	2	1	3	1	5	0	12
Tékhne	0	0	1	0	1	0	2
Tourism Analysis	0	2	0	0	0	0	2
Tourism Economics	1	1	3	9	8	0	22
Tourism Management	4	2	4	8	6	1	25
Tourism Management Perspectives	0	1	1	1	1	0	4
Other Journals	5	3	9	9	3	1	30
Total	13	15	29	36	37	6	136

Note: [ǂ] January and February.
Source: author

Almost all the articles reviewed (90%) were published in indexed scientific journals, and their distribution, in terms of quartiles, shows that only 9% of these are in quartiles three and four of their respective categories (Figure 2). Regarding SJR, SNIP and CiteScore metrics, it can be observed that their means are respectively 1.548, 1.584 and 2.50. In general, the journals of the articles analysed have SNIP 2015 values concentrating between 0.6 and 1.2, but a large percentage, fall above 2.1 (40%). As for the SJR2015 values, although many journals have a value of one in this ranking, 38% are above two. Furthermore, 42% of the journals of reviewed articles have a CiteScore above three (42%). With respect to CiteScore Rank, 66% of the articles are in journals higher than the 33rd place of their category.

Figure 2 - Distribution of scientific journals by quartiles



Source: author

2.2.1. Number of Publications by Author

The academics who have been more productive (i.e. more than three research articles published between 2012 and 2017) in terms of articles on tourism demand modelling are as follows: Faruk Balli (Balli, Balli, & Cebeci, 2013; Balli, Balli, & Jean Louis, 2016; Balli, Curry, & Balli, 2015; Balli & Jean Louis, 2015; Balli & Tsui, 2015; Tsui & Balli, 2015) and Martin Falk (Falk, 2013a, 2013b, 2014; Falk & Hagsten, 2016; Falk & Vieru, 2016a, 2016b) have six published articles; Oscar Claveria (Claveria, Monte, & Torra, 2015a, 2015b, 2015c; Claveria & Torra, 2014), Ulrich Gunter (Gunter, Ceddia, & Tröster, 2017; Gunter & Smeral, 2016; Gunter & Önder, 2015, 2016), Haiyan Song (Li, Song, Cao, & Wu, 2013; Page, Song, & Wu, 2012; Smeral &

Song, 2015; Wan, Song, & Ko, 2016) and Salvador Torra (Claveria et al., 2015a, 2015b, 2015c; Claveria & Torra, 2014) have four publications.

2.2.2. Qualitative versus Quantitative Methods

The two methodological approaches in tourism modelling and forecasting include qualitative analysis and quantitative analysis (Hyndman & Athanasopoulos, 2014). Qualitative methods are used when there are no relevant historical data that can produce good forecasts, or when the patterns that would allow using historical data are no longer present. Qualitative methods of forecasting, are not hints, but rather include very structured methodologies. Qualitative methods used in tourism demand forecasting include the jury of executive opinion, subjective probability assessment, Delphi method and consumer intentions survey (Frechtling, 2001). The application of qualitative methods in tourism demand forecasting can give a better accuracy because of existing volatility in this industry and its elasticity after events (Croce & Wöber, 2011).

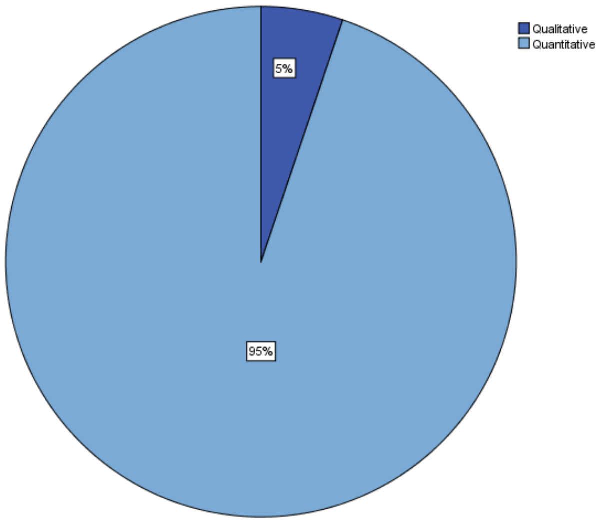
Regarding quantitative methodologies causal and non-causal time series models can be found. First are based on the assumption that what is intended to predict depends on a relationship of cause and effect of one or more variables. On the other hand, the approach using non-causal time series models is based on past information on a variable to generate forecasts. Song and Li (2008), established that tourism demand modelling includes forecasting models based on non-causal models, causal models and, more lately, models that include artificial intelligence, neural network models, among others. The use of this third class of tourism demand models was still infrequent in tourism demand modelling, compared with casual and non-casual time series models (Coshall & Charlesworth, 2011).

Quantitative methods, used to model and estimate tourism demand, are based on the formulation of hypotheses based on the theory of demand, the specification of the model of tourism demand, the collection of data considered relevant to the study, modelling and estimation of tourism demand, testing considered hypotheses, making predictions and assessing the results of the forecast (Dwyer, Forsyth, & Dwyer, 2010).

Regarding quantitative methodologies, journal authors have used, among others, time series models (i.e. regression, forecasting, volatility models and regression models with volatility), neural networks models, panel data models and structural models.

This systematic literature review revealed (Figure 3) that almost all the research on tourism demand modelling published in recent years has used quantitative methods (95%). The qualitative studies analysed, with only one exception, were published in the first and second quartiles of tourism, leisure and hospitality management journals, namely, *Journal of Travel and Tourism Marketing*, *Annals of Tourism Research*, *Journal of Travel Research*, *Tourism Economics* and *International Journal of Commerce and Management*.

Figure 3 - Qualitative versus quantitative research



Source: author

The application of qualitative methods for modelling and forecasting tourism demand has been recently, more frequent. Among the qualitative methods used, this review revealed the travel constraints model (Cheng, Wong, & Prideaux, 2017), the in-depth interviewing (Czernek, 2013), netnography (Ji, Li, & Hsu, 2016), scenario planning (Frost, Laing, & Beeton, 2014), expert forecasting (Croce, Wöber, & Kester, 2015) and Delphi (Kaynak & Rojas-Méndez, 2014) methods. Only one study combined qualitative methodology with a quantitative methodology, using neural networks (Ghaderi, Mat Som, & Wang, 2014). Half of these articles focused only on modelling tourism demand, while the remainder made predictions about tourism demand.

The online marketing information system TourMIS that is used by tourism practitioners since 2000 includes a group forecasting support system that uses the predictions from users based not only on quantitative methods but also on judgements from experts (Croce & Wöber, 2011).

2.2.3. Tourism Demand Modelling Methods

Wong, Song, Witt and Wu (2007), Andrawis, Atiya and El-Shishiny (2011), Shen, Li and Song (2011) and Song et al. (2012) found that a combination of different models can significantly improve the quality of predictions showing that this strategy provides a better forecasting performance than single-method forecasts do.

Quantitative methods of tourism demand modelling can be categorized into groups. These include time series models based on means (i.e. regression), time series models based on variance (i.e. volatility), time series models based on means and variance (i.e. regression and volatility), time series forecasting models, structural models, neural networks, panel data and other quantitative models.

Volatility modelling first appeared in the literature on tourism with Chan, Lim and McAleer's study (2005), in response to the economic, political and financial changes that have required profound modifications of tourism demand models. Overall, the use of the neural networks method to develop tourism demand models has appeared less frequently in research on modelling tourism demand compared with other models (Coshall & Charlesworth, 2011).

Regarding to causal models, according to Morley, Rosselló and Santana-Gallego (2014) gravity models can be applied to evaluate the roll of structural factors and can be an important tool to analyse the policy determinants of tourism demand, such as tourist taxes and promotional expenditure policies.

The potential of using Singular Spectrum Analysis (SSA) was examined by Hassani, Webster, Silva and Heravi (2015) using tourist arrivals into United States of America. These authors found that SSA offers significant advantages than alternatives methods, like Autoregressive Integrated Moving Average, exponential smoothing and neural networks.

Akin (2015) proposed an approach to model selection based on a decision tree that must be constructed after we have identified the components of a time series using STSM. This author used arrival data to Turkey to compare performances of SARIMA, Support Vector Machine and Artificial Neural Networks (ANN) models.

Many studies have modelled tourism demand using time series, like Shareef and McAleer (2007) that analysed arrivals from the eight major tourism source countries using Generalized

Autoregressive Conditionally Heteroscedastic (GARCH) and Glosten-Jagannathan-Runkle (GJR) models. Tourism demand in Taiwan was analysed and forecasted with an adaptive fuzzy time series model by Tsaur and Kuo (2011) and with a SARIMA-GARCH model by Liang (2015) that compared his predictive power regarding other methods. More recently, Hamadeh and Bassil (2017), also applied GARCH models in tourist arrivals series in Lebanon to link fluctuations to terrorism and war.

Valadkhani and O'Mahony (2015a) used a five-variable Vector Autoregressive (VAR) model to model tourism demand from Australia's five principal markets and they could understand the dynamic interplay between them. This allowed concluding that Australia should diversify cross-country tourism portfolios to minimize volatility of inbound tourism.

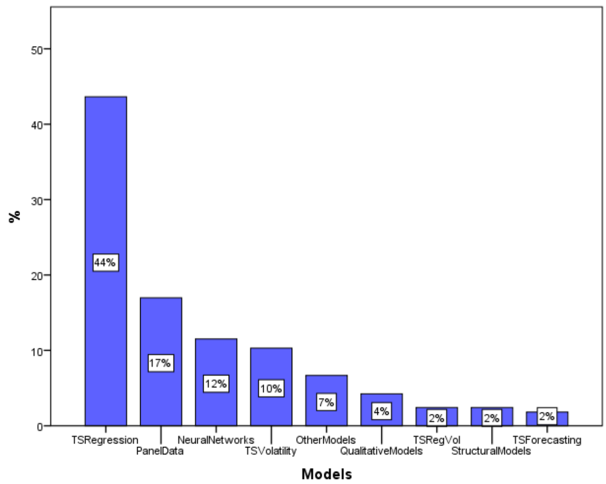
Panel Generalized Least Squares models have been used to determine factors that influences tourism demand from Australians (Yap, 2013).

In Portugal, Serra, Correia and Rodrigues (2014), estimated dynamic panel data models to explain the evolution of international overnight stays in each region from main tourism source markets for Portugal (The United Kingdom, Germany, The Netherlands, Ireland, France and Spain) using per capita income, unemployment rate and final household consumption as explanatory variables.

Berenguer, Berenguer, García, Pol and Moreno (2015) used ANN in mature and nonconsolidated destinations with a model that uses time series, different arrival seasons and values of months with similar behaviour. This type of model turned out to be much more accurate towards the most time-series models and, this supremacy, proved better, especially in non-consolidated destinations. Also Claveria et al. (2015a) applied a multivariate neural network that incorporates common trends in inbound international tourism from all visitor markets to a specific destination. In Portugal, Teixeira and Fernandes (2014) used tourism revenue and overnight stays in North region hotels to analyse the performance of dedicated ANN and found a very good forecasting quality in these type of models.

With respect to the distribution of articles by type of methodology (Figure 4), the present review revealed that the models most used in published studies are time series regression models (44%), followed by panel data models (17%). Neural networks models appear in 12% of the articles analysed. Volatility models are used only in 10% of the studies and volatility with regression models in 2%.

Figure 4 - Distribution of scientific articles by type of model



Source: author

Regarding the objectives of each study, the articles reviewed can be divided into the following classifications: those that sought to: (a) model tourism demand, (b) develop a model to meet forecasting objectives and (c) model the volatility of tourism demand.

According to Table 3, the researchers, seeking to model tourism demand, mainly used time series regression and panel data models. The studies that sought to forecast tourism demand primarily used time series regression and neural networks models. The research focused on modelling the volatility of tourism demand mainly used time series methods (i.e. models in mean and models in variance).

Table 3 - Distribution of type of models by type of study

Type of Study		TS Regression	TS Volatility	TS RegVol	TS Forecasting	Neural Networks	Panel Data	Structural Models	Other Models	Qualitative Models
		Type of Models								
Type of Study	Modelling	39	8	0	0	2	23	3	9	4
	Forecasting	28	3	1	3	16	2	1	2	3
	Volatility	11	16	4	0	1	3	0	1	0

Notes: TS: time series; RegVol: regression and volatility.
Source: author

2.2.4. Variables in Tourism Demand Modelling

Schwaninger (1984) analysed trends in tourism for twenty years, juxtaposing the demand growth with changes in the economy, consumer behaviour and technology. The cited author highlighted the need for long-term monitoring the links between these factors and growth trends in tourism. Chew (1987), in turn, concluded that growth trends in tourism may be affected by economic downturns, after the cited author analysed factors that can influence tourism, highlighting others with greater weight. Shareef and McAleer (2005) have modelled volatility of tourism in small islands through log analysis of international arrivals and growth rates of international arrivals, stating that volatility is a measure of the variation of price or return, where periods of high volatility are followed by low volatility periods, and vice versa. Song et al. (2012) found that the number of arrivals and the level of tourism expenditure were the most commonly variables used to measure tourism demand.

When modelling tourism demand, researchers, most often, have used variables related to tourist arrivals, with 53% of the papers analysed including this variable in their models. In addition, studies have used the number of visitors separated into global, holiday and business travellers (A. Liu & McKercher, 2016) or museum (C.-M. Chen & Chang, 2016) and temple visitor (J.-C. D. Chang & Chen, 2013). Still other variables include repeat visitors (McKercher & Tse, 2012), those from different source markets (i.e. by country or continent), overnight stays, length of stay (Culiuc, 2014; Falk, 2013b) and international tourism flows.

Variables related to tourism expenditure and receipts are used in 22% of studies under analysis, when modelling tourism demand. These variables include, for example, ski lift revenue (Falk & Vieru, 2016a), vacation rental revenue (Ritchie, Crotts, Zehrer, & Volsky, 2013), observed average spending per day (Divisekera, 2016), hotel room revenue (Ritchie et al., 2013) and air transport and accommodation spending categories (Becken & Lennox, 2012).

Askitas and Zimmermann (2015) compiled the most relevant literature in this field, using Internet data to conduct social sciences research. The cited authors found applications of this type of data, from 2005 onwards, in studies that analysed and predicted unemployment and engaged in nowcasting in terms of health, labour and demographic issues and political processes. These authors predict that researchers will soon frequently apply this type of data. This kind of data bargains new opportunities in tourism research. Big Data is a new concept that has become common in recent years to describe the production of massive quantities of data and covers a range of different areas, like Internet searches, bank card transactions, records of mobile phone activity, social networks and images recorded with video cameras (Salas-Olmedo, Moya-Gómez, García-Palomares, & Gutiérrez, 2018).

However, the use of Internet data in tourism demand modelling is still relatively rare (7% of the articles analysed). These studies include data from Google Analytics (Gunter & Önder, 2016), Internet search data (Jackman & Naitram, 2015), metadata from tagged photos (Onder, Koerbitz, & Hubmann-Haidvogel, 2016), website traffic (Pan & Yang, 2016) and click-throughs (Pan, 2015). Recently, Dergiades, Mavragani and Pan (2018) used data from search engines to model tourism demand for Cyprus, based on the United Kingdom, Russia, Greece, Germany and Sweden markets, concentrating on a correction of this type of analysis in order to reduce the biases from search engine language and search engine platform used and Salas-Olmedo et al. (2018) compared Big Data sources to analyse the presence of tourists in cities.

More globally, the most commonly used variables are prices (38% of the reviewed articles), namely, substitution, export and import and consumer price indexes. Other variables also common in determining tourism demand are GDP (37%); exchange rates (27%); sociodemographic and territorial variables such as unemployment (7%); income (7%); population (7%) and distance between countries (5%). Availability in the tourism industry in terms of hotels, by means of beds and rooms, (Balli et al., 2013; Culiuc, 2014; Habibi, 2017;

Laframboise, Mwase, Park, & Zhou, 2014) and airlines via seats and presence of direct flights (Deluna & Jeon, 2014; Nonthapot & Lean, 2015) are additional variables used in tourism demand modelling.

Political factors, such as the openness of economies, political instability, fiscal policies, indexes of political rights and civil liberties and indexes that measure civil liberties across countries are also considered in the studies analysed (Balli & Jean Louis, 2015; Habibi, 2017; Pavlic, Svilokos, & Tolic, 2015; Saha & Yap, 2014; Su & Lin, 2014). The use of dummy variables is extremely commonly used in this type of research to control language issues (Balli et al., 2013; Balli et al., 2016; De Vita, 2014; Deluna & Jeon, 2014; Saayman, Figini, & Cassella, 2016) and political factors, as ‘free’ countries, colonial relationships and free trade agreements (Balli et al., 2013; Balli et al., 2016; De Vita, 2014). Other dummy variables address the effects of crises, like economic downturns, epidemics, calamities, terrorism and wars (Deluna & Jeon, 2014; A. Liu & Pratt, 2017; Nonthapot & Lean, 2015; Otero-Giráldez, Álvarez-Díaz, & González-Gómez, 2012; Smeral & Song, 2015; Yap, 2013) and events like the Olympics and championships (Herrmann & Herrmann, 2014; Smeral & Song, 2015). Models used up to 14 variables of this type (Smeral & Song, 2015).

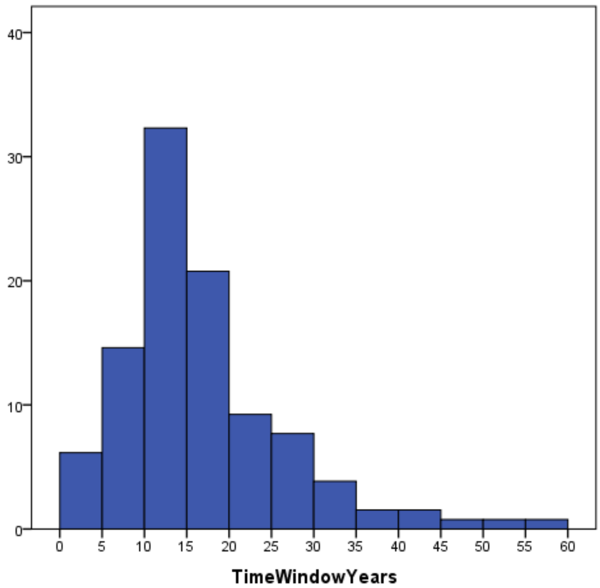
Climate-related variables are included as determinants of tourism demand. These can be precipitation, weather information, temperature, snow depth, rainfall, meteorological conditions and cloud coverage (Agiomirgianakis, Serenis, & Tsounis, 2017; Alvarez-Díaz, González-Gómez, & Otero-Giráldez, 2015; R. Chen et al., 2015; Falk, 2013a, 2014; Falk & Hagsten, 2016; Falk & Vieru, 2016a; Pan & Yang, 2016; Ridderstaat, Oduber, Croes, Nijkamp, & Martens, 2014).

2.2.5. Data Frequency

In tourism modelling, literature distinguish between three different time horizons according to the objectives of development policies and planning: short time modelling covers a year or less and it allows managers to make decisions about current operations, an intermediate run that includes forecasting in two to five years and it is used in expansions and changes in products or services and the long-range forecasting is indicated to tourism planning and policies development and it includes at least over a five years analysis (Dwyer et al., 2010).

In the studies revised, the time window varied from one to 56 years, and more than 50% of them covered between 10 and 20 years when modelling tourism demand (Figure 5).

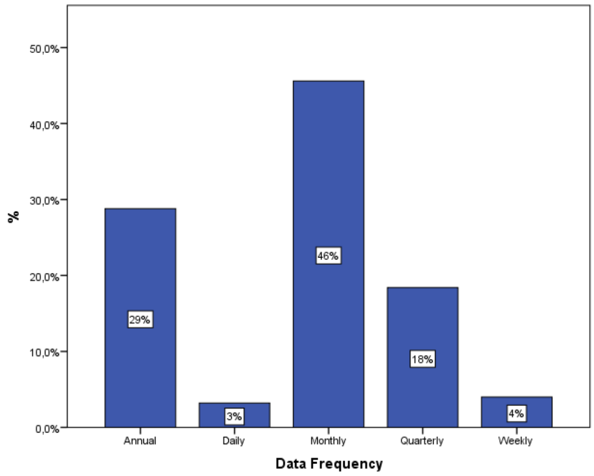
Figure 5 - Distribution of time window (years) used in analysed studies



Source: author

The variables used were measured for different time frequencies (Figure 6). The most common was a monthly (46%) or annual (29%) frequency. The least used time frequency was daily data (3%) (C.-L. Chang, Hsu, & McAleer, 2013; R. Chen et al., 2015; Ellero & Pellegrini, 2014; Herrmann & Herrmann, 2014).

Figure 6 - Distribution of articles by data frequency



Source: author

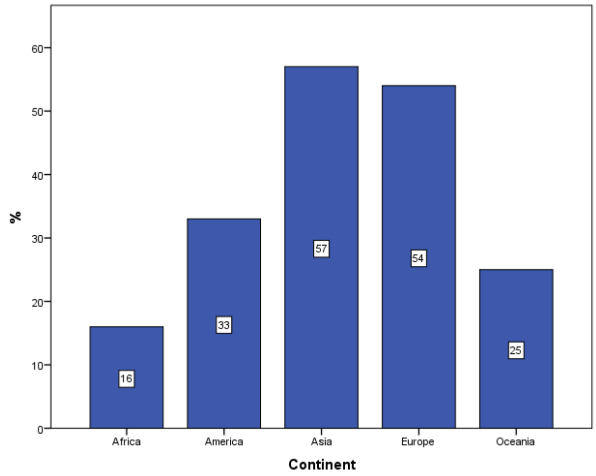
2.2.6. Tourism Demand Modelling in the World

Research on tourism demand modelling varies greatly with respect to type of territory. The present review found that some studies were done in all countries simultaneously, such as research conducted by Gunter and Smeral (2016) and Croce (2016). Other studies covered continents, including Smeral and Song (2015) in Europe and Frost et al. (2014) in Asia-Pacific. Single country research made up 70% of the articles analysed. Regional studies were conducted by, for example, Crotts and Mazanec (2013) in Florida, Berenguer et al. (2015) in Santa Lucía de Cuba and the North Region of Portugal, and Neves, Fernandes and Pereira (2015) in several Portugal regions. Teixeira and Fernandes (2014) also did research in the North Region of Portugal; Guizzardi and Stacchini (2015) in Rimini, Italy; and Otero-Giráldez et al. (2012) in Galicia, Spain.

Many researchers focused on cities, including Önder and Gunter (2016) in Vienna, Austria; Gunter and Önder (2015) in Paris, France; Süssmuth and Woitek (2013) and Herrmann and Herrmann (2014) in Munich, Germany; and Ellero and Pellegrini (2014) in Milan, Rome and Turin, Italy. Some studies covered small destinations, such as Falk (2013a, 2013b), Falk and Hagsten (2016) and Falk and Vieru (2016a) in ski areas in Austria, Finland, Sweden and Switzerland, and Czernek (2013) in a southern mountain tourism region in Poland.

The present systematic literature review revealed that, since 2012, the existing studies have covered the five continents but have main concentrated on Asia (57%) and Europe (54%). The continent on which the least research has been carried out is Africa, with only 16% of the articles modelling tourism demand for African destinations (Figure 7).

Figure 7 - Distribution of analysed studies by continent (object of the study)



Source: author

The countries on which more research on forecasting tourism demand are Australia, Spain, the United States of America, China, Hong Kong (Special Administrative Region of China), Austria, Portugal, Taiwan, Thailand, Turkey, Aruba, Germany, Italy, New Zealand, Singapore and the United Kingdom (Table 4). Each of these nations has been the focus of three or more studies.

Table 4 - Reviewed articles by authors, year of publication and country analysed

Authors (Year)	**Country**
Culiuc (2014) Balli and Jean Louis (2015) Croce et al. (2015) Saha and Yap (2014) Ghaderi, Saboori and Khoshkam (2016) Jackman (2014) Balli et al. (2016) Saayman et al. (2016) Lv and Xu (2016) Su and Lin (2014) Liu and Pratt (2017) Frost et al. (2014) Laframboise et al. (2014) Nowak, Petit and Sahli (2012) Antonakakis, Dragouni and Filis (2015) Nonthapot and Lean (2015) Gunter and Smeral (2016) Croce (2016)	World, Continent or Multiple Countries
Ridderstaat, Croes and Nijkamp (2014) Ridderstaat, Oduber et al. (2014) Ridderstaat and Nijkamp (2015)	Aruba
Assaf, Gil-Alana and Barros (2012) Seetaram (2012) Yap (2013) De Vita (2014) Dwyer, Pham, Jago, Bailey and Marshall (2014) Balli and Tsui (2015) Tsui and Balli (2015) Valadkhani and O'Mahony (2015a, 2015b)	Australia

Authors (Year)	**Country**
Divisekera (2016) Tan, Koo, Duval and Forsyth (2016) Wu, Liu, Hsiao and Huang (2016)	Australia
Falk (2013a, 2014) Gunter and Önder (2016) Önder and Gunter (2016) Önder et al. (2016) Vergori (2016)	Austria
Lorde and Jackman (2013) Jackman and Natiram (2015)	Barbados
Kaynak and Rojas-Méndez (2014)	Chile
Deng, Ma and Shao (2014) Yang, Liu and Qi (2014) Zhou-Grundy and Turner (2014) R. Chen et al. (2015) Yang, Pan, Evans and Lv (2015) Sun, Sun, Wang, Zhang and Gao (2016) Tang, King and Pratt (2016)	China
Gunter et al. (2017)	Costa Rica
Mamula (2015) Pavlic et al. (2015)	Croatia
Berenguer et al. (2015)	Cuba
Can and Gozgor (2016)	Egypt
Falk and Vieru (2016a, 2016b)	Finland
Gunter and Önder (2015)	France
Süssmuth and Woitek (2013) Herrmann and Herrmann (2014) Ahlfeldt, Franke and Maennig (2015)	Germany
Choi and Varian (2012) McKercher and Tse (2012) Wu, Law and Xu (2012) Li et al. (2013) Liu and McKercher (2016) Tang, King et al. (2016) Wan et al. (2016)	Hong Kong
Agiomirgianakis, Serenis and Tsounis (2015)	Iceland
Kuncoro (2016)	Indonesia
Ellero and Pellegrini (2014) Guizzardi and Stacchini (2015) Baggio and Sainaghi (2016)	Italy
Bangwayo-Skeete and Skeete (2015)	Jamaica
Ji et al. (2016) Cheng et al. (2017)	Japan
Kim, Park, Lee and Jang (2012) Park, Lee and Song (2017)	Korea
Ghaderi et al. (2014) Habibi (2016)	Malaysia
Constantino, Fernandes and Teixeira (2016)	Mozambique
Becken and Lennox (2012) Balli et al. (2015) Dekimpe, Peers and van Heerde (2016)	New Zealand
Raza and Jawaid (2013)	Pakistan
Deluna and Jeon (2014)	Philippines
Czernek (2013)	Poland
Daniel and Rodrigues (2011) Teixeira and Fernandes (2012) Serra et al. (2014) Teixeira and Fernandes (2014) Neves et al. (2015) Andraz and Rodrigues (2016)	Portugal
Liu, Sriboonchitta, Nguyen and Kreinovich (2014) Zhu, Lim, Xie and Wu (2016)	Singapore

Authors (Year)	Country
Agiomirgianakis et al. (2017)	Singapore
Saayman and Botha (2015) A. Saayman and Saayman (2015)	South Africa
Otero-Giráldez et al. (2012) Claveria and Torra (2014) Perles-Ribes, Ramón-Rodriguez, Sevilla-Jiménez and Rubia (2014) Alvarez-Díaz et al. (2015) Artola, Pinto and Garcia (2015) Claveria et al. (2015a, 2015b, 2015c) Morales and Devesa (2015) Albaladejo, González-Martínez and Martínez-Garcia (2016)	Spain
Fernando, Bandara, Liyanaarachch, Jayathilaka and Smith (2013)	Sri Lanka
Falk and Hagsten (2016)	Sweden
Falk (2013b)	Switzerland
C.-L. Chang, McAleer and Lim (2012) C.-L. Chang et al. (2013) J.-C. D. Chang and Chen (2013) Liang (2014) C.-M. Chen and Chang (2016)	Taiwan
Bunnag (2014) Tang, Sriboonditta, Yuan and Wu (2014) Untong, Ramos, Kaosa-Ard and Rey-Maquieira (2014) Bunnag (2015) Untong, Ramos, Kaosa-Ard and Rey-Maquieira (2015)	Thailand
Bronner and de Hoog (2016)	The Netherlands
Akar (2012) Balli et al. (2013) De Vita and Kyaw (2013) Agiomirgianakis, Serenis and Tsounis (2014) Akin (2015)	Turkey
Page et al. (2012) Cang (2014) Pérez-Rodríguez, Ledesma-Rodríguez and Santana-Gallego (2015)	United Kingdom
Crotts and Mazanec (2013) Ritchie et al. (2013) Hassani et al. (2015) W. S. Lee, Moon, Lee and Kerstetter (2015) Pan (2015) Smeral and Song (2015) Dragouni, Filis, Gavriilidis and Santamaria (2016) Pan and Yang (2016) Gozgor and Ongan (2017)	United States of America

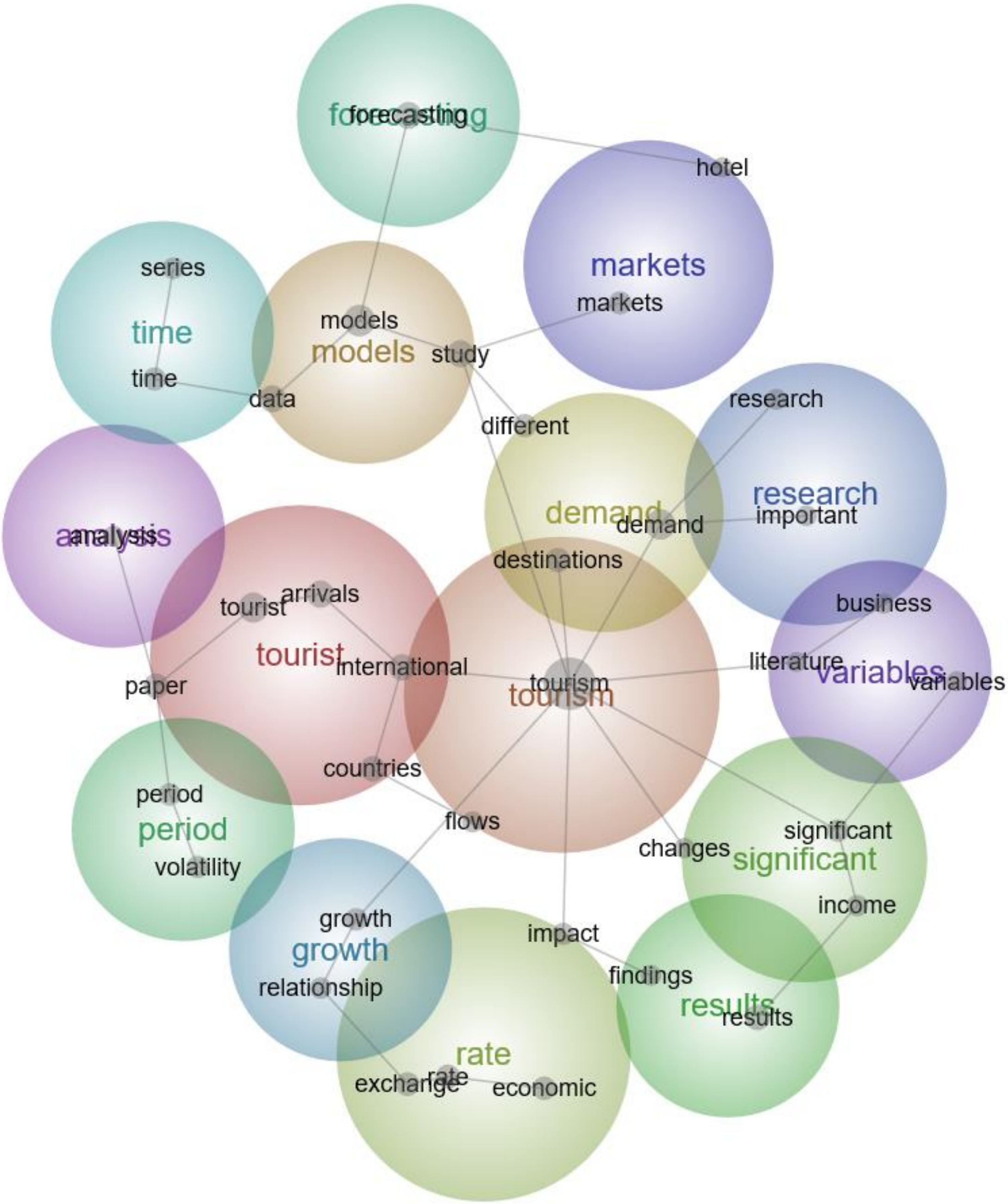
Source: author

2.2.7. Semantic Analysis

Regarding the keywords in the articles analysed, 77% of the articles used keywords related to tourism flows (i.e. tourism demand, tourism flows, tourist arrivals and tourism data), 30% had keywords about financial or economic factors (i.e. exchange rate, income, expenditure and receipts), while 27% included forecasting (i.e. tourism demand and short-term forecasts) and 21% mentioned security, crises and risks. In addition, 13% of the articles’ keywords focused on seasonality (i.e. seasonal patterns and SARIMA), 13% mentioned Internet data (i.e. Google, Internet searches and websites), and 13% dealt with panel data models. Finally, 10% of the articles' keywords included neural networks, as well as 7%, respectively, for Autoregressive Conditionally Heteroscedastic (ARCH) methods, volatility, time series and climate conditions.

An analysis using Leximancer© (Version 4.5) software produced 37 concepts grouped into 15 themes (Figure 8). The most prominent themes are 'tourism', 'tourist', 'models' and 'demand', which are consistent with the results of the keyword analysis. These four themes include the following concepts: 'tourism', 'models', 'demand', 'tourist', 'data', 'study', 'arrivals', 'international(ity)', 'countries', 'paper', 'destinations', 'difference' and 'flows'. One of the emergent themes (i.e. least prominent themes) is 'period', which is linked with the concepts 'period' and 'volatility' and closer to the themes 'tourist', 'growth' and 'analysis'.

Figure 8 - Concept map



Source: author

2.3. Concluding Remarks

This literature review revealed the importance of tourism in cities and the importance of tourism demand modelling on a more precise geographic scale, allowing a better planning and management of this type of tourism destination, and adapting decisions to each source market.

The importance of tourism in cities, particularly in Europe, and the lack of studies on tourism demand volatility, at the cities scale, in Portugal, despite the institutional assumption of the importance of this type of tourism in our country, revealed the way for this research.

It was conducted presenting the main forecasting methods applied to tourism demand, as well as the most recent studies in which they were used. Moreover, the review showed that modelling volatility is an emergent approach used in the analysis of tourism demand time-series. These results revealed pathways for the use of volatility models in tourism demand studies, which will allow managers and decision makers to adapt the policies dealing with the volatility associated with tourism demand. Recent studies that applied volatility models to tourism demand were essentially applied in Asia and Oceania and, also in the USA, clearly showing a gap in the use of such models in Europe tourism destinations.

This chapter allowed the identification of the need to model tourism demand using models of volatility, not only because it is an emerging theme, in recent scientific literature, but because the commitment assumed in linear models of the existence of constant variance may not be verified in tourism demand, where, as in the financial markets, the reaction to good news and bad news, can change behaviours on mean, but also in variance.

The systematic review of the recent literature on this topic specifically targeted models used to analyse tourism demand and allowed an alternative classification of the methods. It permitted to identify the possibility of using monthly data, referring to overnight stays and with a temporal window included in the observed modal class. The literature revealed, also, some determinants of volatility in the tourism industry, such as income, GDP and exchange rates, as well as crime, major events, big shocks, epidemics, weather conditions and the absence or existence of direct flights.

The conditional heteroscedasticity models were identified as the appropriate methodology for the modelling of volatility in time series, which will be briefly described in the next chapter.

3. Methodology

The methodology is divided into five sections, beginning with the research paradigm and the identification of the study object, namely, the three cities and the source markets. The second section shows the conceptual framework of this research and the third makes a contextualization of the research, in the tourism market in Portugal, namely, tourism in the three cities previously identified.

A description of the database used, the transformations carried out on the original data and some preliminary statistical tests on the data is given below. Finally, the three types of conditional heteroscedasticity models used in this thesis are described.

3.1. Research Paradigm

The approach of this research, that involves quantitative data, based on an objective and deductive process, with a high degree of structure, is the positivism paradigm.

The prospective diagnosis given by Turismo de Portugal (2015) had identified, in the seven regions within Portugal, the main tourism resources, as follows:

• In Oporto and North region (with 49% of residents' overnight stays and Spain, France, Brazil, Germany and the United Kingdom as main inbound markets) it has been appointed the tourism resource Oporto;

• In Centre region (with 60% of residents' overnight stays and Spain, France, Germany, Brazil, and Italy as main inbound markets) it has been appointed the tourism resource Coimbra;

• In Lisbon region (with 24% of residents' overnight stays and Spain, France, Brazil, Germany and the United Kingdom as main inbound markets) it has been appointed the tourism resource Lisbon;

• In Alentejo, Algarve, Azores and Madeira regions the element 'city' has not been appointed as a tourism resource.

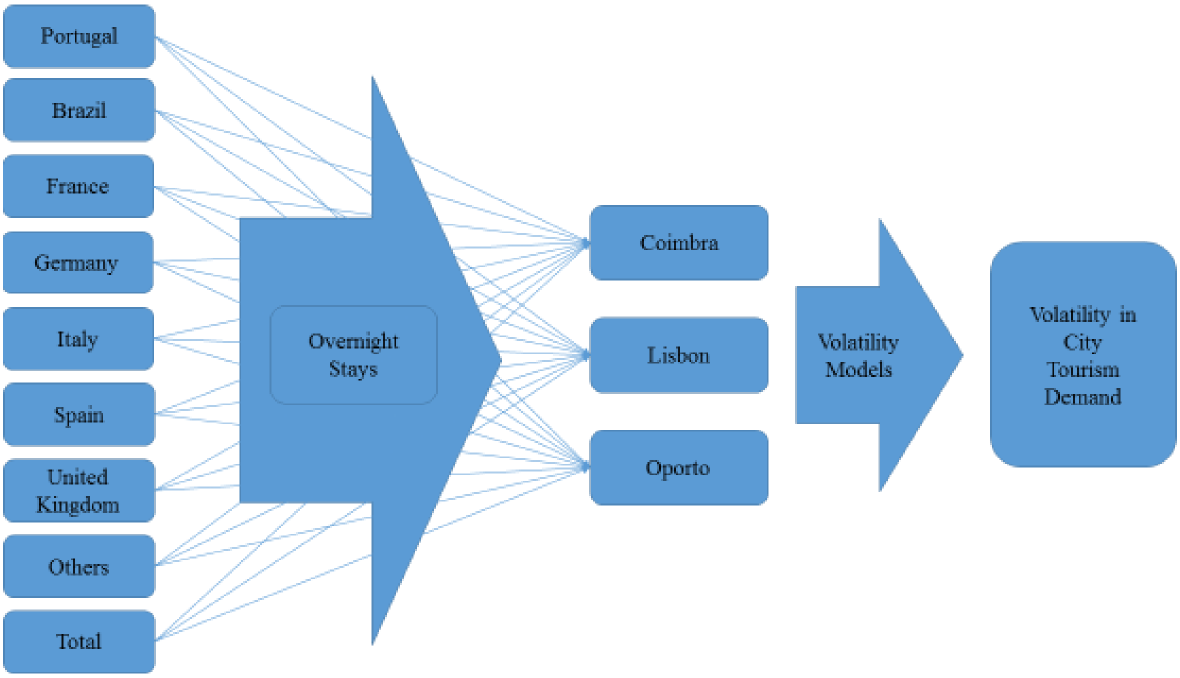
Cities to be studied were identified, as well as the source countries and the methods to be applied. Thus, in this research, the domestic tourism demand and that from major emitting countries will be analysed in order to understand the existence of volatility in Coimbra, Lisbon and Oporto tourism demand.

The identified source markets Brazil, France, Germany, Spain and the United Kingdom, are considered strategic markets in Portugal and Italy is considered a growth market (Turismo de Portugal, 2017).

3.2. Conceptual Framework

The conceptual framework of this study (Figure 9) includes modelling volatility according to tourism demand data among the top six source countries and Portugal (domestic tourism) in the cities of Coimbra, Lisbon and Oporto. Based on these models, we intend to measure volatility related to tourism in these cities.

Figure 9 - Conceptual framework



Source: author

The state of art covered existing forecasting methods and studies in tourism, which have already implemented them. No single method can be considered the best in all contexts because, even within a region, the best model varies between different source markets (Gunter & Önder, 2015). Thus, it is important to test the accuracy of two or more models when we want to achieve good models that can assist in the development of tourism planning policies. Methods that can be applied to the modelling of tourism demand and volatility are very dependent on the availability of data and the possibility of comparability. According to the type of data available and the objectives of this research, autoregressive conditionally heteroscedastic models seem to be the adequate one to analyse volatility.

3.3. Research Context

Portugal is located in the largest tourism region in the world, Europe, which accumulates about 51% of international tourism and around 34% of revenues. The early stages of tourism in Portugal was in the beginning of the 20th century (Table 5) but only in the 1950s and 1960s, Portugal recorded the first economic development based on mass tourism. The National Tourism Plan in 1986 pointed out the first change in tourism policy and in the 1990s the Portuguese government begin to host a sequence of major events that continued into the following decade, namely, Lisbon's year as European Capital of Culture, in 1994, the Lisbon International Exhibition in 1998, Oporto's year as European Capital of Culture in 2001 and the UEFA European Football Championship in 2004 (Almeida Garcia, 2014; Turismo de Portugal, 2015).

Table 5 - Early stages of Tourism in Portugal

Year	Early stages of Tourism in Portugal	Key factors
1905	Society Propaganda of Portugal Tourism initiative associations	The first private initiatives
1911	National Propaganda and Tourism Department	The first government initiatives
1911	IV International Congress of Tourism in Lisbon	
1930	Portuguese Commission for the Promotion of Tourism	Other government agencies
1942	1st Pousada (State hotel chain) Elvas	Improved hotel accommodation

Source: adapted from Almeida Garcia (2014)

In 2015, Portugal was the 26th country in the ranking of tourism revenues. In terms of competitive positioning, with regard to travel and tourism, Portugal was, in 2013, in 20th place and third relative to its main competitors: first Spain, second France, and fourth Italy, among others, and in 2015, 2016 e 2017 it has been in the Top15 of the most competitive countries in the world (Turismo de Portugal, 2015, 2017; World Economic Forum, 2017).

The evolution of total overnight stays in Portugal, those from domestic tourism, from the five countries analysed specifically in this research and from other non-specified countries, is summarized in Table 6 for the years that will be studied. Since 2001, total overnight stays have increased by 76%, and, among the analysed markets, the highest increase occurred with the Brazilian market, which more than quadrupled the number of overnight stays between 2001 and 2016. In the European markets under analysis, the highest increase occurred with the French market, which more than quadrupled the number of overnight stays in Portugal and the lowest increase occurred with overnight stays coming from Germany. The United Kingdom is the market that has the largest tourism market share in terms of overnight stays.

Table 6 - Annual evolution of overnight stays in Portugal by source market (in thousands)

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
World	33563	34209	33875	34141	35521	37567	39737	39228	36457	37391	39440	39681	43533	48711	53074	59123
Portugal	9985	10646	10661	11139	11648	12350	12968	13024	13243	13783	13437	12424	13151	14939	16158	17352
Brazil	346	325	300	336	411	462	559	673	596	829	1015	1139	1235	1436	1413	1623
France	1046	1156	1202	1093	1112	1241	1442	1590	1595	1619	1931	2225	2691	3231	3679	4413
Germany	4532	4105	3899	3772	3899	3863	3851	3658	3342	3279	3392	3685	4274	4643	5219	5807
Italy	799	780	722	738	723	953	1011	929	803	869	918	867	834	928	1155	1308
Spain	1913	2068	2154	2393	2726	3195	3381	3069	3204	3278	3445	3077	3216	3740	3940	4324
United Kingdom	7267	7406	7385	7080	7378	7258	7705	7302	5670	5495	6259	6422	7101	7775	8610	9582
Others	7675	7722	7552	7589	7624	8245	8820	8983	8005	8239	9043	9842	11032	12019	12899	14714

Note: Others are non-specified countries

Source: adapted from Statistics Portugal (Instituto Nacional de Estatística, 2002, 2004a, 2004b, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017)

Portugal presented a solid performance in 2016, with international guest arrivals in accommodation establishments growing 12% (UNWTO, 2018a) and, that year, was marked by historical results for national tourism in the main indicators: overnight stays, revenues, guests, employment and exports, and tourism was considered the largest economic activity with 16.7% of exports (Turismo de Portugal, 2017).

The modelling of tourism demand in Portugal has been carried out only to regional disaggregation level and there are no predictive models developed for cities, which have been recognized as important tourism resources for some regions (Turismo de Portugal, 2015). One of the action lines to value territory and communities in Portugal, is to promote the urban regeneration in cities and regions, and the sustainable tourism development of territories and destinations (Turismo de Portugal, 2017). In Portugal, data for more disaggregated destinations than the tourism regions level (county level, city level or local level) are not available to the general public in the official site and non-provisional data are available only one year after they have occurred.

Due to the increasing importance of tourism, Portugal is the object of this research. The action plan for the development of tourism in Portugal - Turismo 2020 - identified three cities in three regions, as a tourism resource: Lisbon, Coimbra and Oporto. In the regions where these cities are included, the main markets, apart from the domestic market, are Spain, France, Brazil, Germany, Italy and United Kingdom (Turismo de Portugal, 2015). Three of these countries are in the world's Top5 of tourism spenders, namely, Germany, United Kingdom and France (UNWTO, 2018b). With the appropriate data, suitable modelling methodologies will be implemented. Based on these models, the volatility of tourism demand, among the three cities and emitting countries will be compared.

3.4. Data Base Description

Time series data are information that have been collected over a period of time on one or more variables and have associated with them a particular frequency of observation or collection of data points. The frequency is simply a measure of the interval over, or the regularity with which, the data are collected or recorded (Brooks, 2014). In this research, monthly, overnight stays data that cover the period from January 2001 to December 2016, for Coimbra, Lisbon and Oporto from Portugal, Brazil, France, Germany, Italy, Spain and the United Kingdom, are employed to explore the existence of volatility in tourism demand. Total overnight stays data and data from other countries were also analysed. Data were obtained from Statistics Portugal.

Table 7 summarizes the descriptive statistics of monthly overnight stays in Coimbra. It can be observed that the main source market, in this city, is the domestic market, followed by the Spanish market, which presents the highest mean among inbound markets. The lowest mean occurs with United Kingdom (which is not one of the main inbound markets in Coimbra) followed by Germany. The coefficient of variation, which results from the quotient between standard deviation and mean, presents high values (greater than 50%) for all markets, which indicates a large relative dispersion of data and little representativeness of the mean, except for the domestic market and for total overnight stays.

In the analysis of skewness, overnight stays from all source markets in Coimbra have positive asymmetry, that is to say, distributions have elongated right tails. All distributions are leptokurtic.

The Jarque-Bera statistic allowed the rejection of the hypothesis of time series having a normal distribution for all source markets at the usual levels of significance.

Table 7 - Descriptive statistics for monthly overnight stays from all analysed source markets in Coimbra (January 2001-December 2016)

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Mean	15129	2021	1454	1124	1926	3946	555	5210	31384
Median	14530	1540	1159	1010	1384	3082	502	4804	30926
Maximum	25401	8691	7140	4369	10208	16749	2269	17799	70082
Minimum	9937	254	178	103	237	813	124	1252	15441
Std. Dev.	3092	1494	1246	846	2067	2776	341	3132	11068
Coef. of Var.	0.21	0.74	0.86	0.75	1.07	0.70	0.61	0.60	0.35
Skewness	0.743	1.415	1.559	0.861	2.367	1.929	1.451	1.298	0.878
Kurtosis	3.084	5.188	6.137	3.494	8.568	7.446	6.366	4.948	3.903
Jarque-Bera	17.72***	102.39***	156.52***	25.69***	427.33***	277.22***	157.99***	84.30***	31.20***
Sum	2904701	387990	279219	215883	369711	757629	106537	1000383	6025721
Sum Sq. Dev.	1.83E+09	4.26E+08	2.96E+08	1.37E+08	8.16E+08	1.47E+09	22202522	1.87E+09	2.34E+10

Notes: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

Descriptive statistics of monthly overnight stays in Lisbon are summarized in Table 8 where it can be observed that the main source market, in this city, is the domestic market, followed by the Spanish market, which presents the highest mean among inbound markets, both like in

Coimbra. The lowest mean occurs with United Kingdom (like in Coimbra) followed by Italy (which is not one of the main inbound markets in Lisbon). The coefficient of variation presents moderate values (about 50%) for almost all markets, which indicates a moderate relative dispersion of data, except for the domestic market and for total overnight stays, as in Coimbra, and for Brazil and France where this coefficient is higher and so we have a little representativeness of the mean.

In the analysis of skewness, overnight stays from all source markets in Lisbon have positive asymmetry, that is to say, distributions have elongated right tails. All distributions are leptokurtic except for domestic market where the distribution of overnight stays is platykurtic.

The Jarque-Bera statistic allowed the rejection of the hypothesis of time series having a normal distribution for all source markets at the usual levels of significance.

Table 8 - Descriptive statistics for monthly overnight stays from all analysed source markets in Lisbon (January 2001-December 2016)

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Mean	129291	37329	42294	38394	33740	65628	27692	165430	539802
Median	126746	29782	32723	37140	29700	56014	26442	143806	494034
Maximum	212653	107641	171295	108473	100507	180386	64837	421161	1233056
Minimum	83736	8711	11416	10186	12774	27470	9568	53174	249716
Std. Dev.	25578	22713	27712	19432	16540	31479	11163	82635	199667
Coef. of Var.	0.20	0.61	0.66	0.51	0.49	0.48	0.40	0.50	0.37
Skewness	0.844	0.802	1.885	1.103	1.896	1.746	1.129	1.180	1.108
Kurtosis	3.633	2.599	6.740	4.297	6.757	5.984	4.555	3.948	4.059
Jarque-Bera	26.00***	21.89***	225.59***	52.40***	227.95***	168.80***	60.12***	51.71***	48.28***
Sum	24823856	7167128	8120392	7371697	6477999	12600516	5316796	31762506	1.04E+08
Sum Sq. Dev.	1.25E+11	9.85E+10	1.47E+11	7.21E+10	5.23E+10	1.89E+11	2.38E+10	1.30E+12	7.61E+12

Notes: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

Table 9 shows descriptive statistics of monthly overnight stays in Oporto. It can be observed that the main source market, in this city, like in Coimbra and Lisbon, is the domestic market, followed by the Spanish market, which presents the highest mean among inbound markets. The lowest mean occurs with Italy (which is not one of the main inbound markets in Oporto), followed by United Kingdom (both like in the other two cities). The coefficient of variation presents high values (greater than 50%) for all markets, which indicates a large relative dispersion of data and little representativeness of the mean, except for the domestic market and for total overnight stays, as in the other two cities.

In the analysis of skewness, overnight stays from all source markets in Oporto have positive asymmetry, that is to say, distributions have elongated right tails. All distributions are leptokurtic except for domestic market where the distribution of overnight stays is platykurtic (like in Lisbon).

The Jarque-Bera statistic allowed the rejection of the hypothesis of time series having a normal distribution for all source markets at the usual levels of significance.

Table 9 - Descriptive statistics for monthly overnight stays from all analysed source markets in Oporto (January 2001-December 2016)

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Mean	47703	8647	11068	7197	6089	21419	6259	31193	139631
Median	46949	6195	7191	5646	4879	17459	5770	24251	119337
Maximum	71103	35866	50147	28545	24353	99590	20608	114404	376470
Minimum	30591	929	1226	1531	1050	4788	1404	6856	51127
Std. Dev.	9277	6844	10170	5430	4610	14659	3720	22384	67030
Coef. Of Var.	0.19	0.79	0.92	0.75	0.76	0.68	0.59	0.72	0.48
Skewness	0.472	1.104	1.732	1.770	1.975	2.201	1.595	1.541	1.305
Kurtosis	2.645	3.646	5.515	6.221	7.047	9.677	6.153	5.121	4.425
Jarque-Bera	8.13**	42.36***	146.62***	183.30***	255.89***	511.73***	160.97***	112.02***	70.73***
Sum	9158918	1660171	2125138	1381905	1169068	4112543	1201656	5988995	26809067
Sum sq. Dev.	1.64E+10	8.95E+09	1.98E+10	5.63E+09	4.06E+09	4.10E+10	2.64E+09	9.57E+10	8.58E+11

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

Sporadic or occasional events were revised, since the objective of this research is to analyse the behaviour of the variance and not the mean. Interpolation was performed according to similar year/month data.

In many problems, the starting point is a time series but, for statistical reasons, it is preferable not to work directly with the original series, so that series are usually converted into series of returns. Additionally, variations in original series, or ‘returns’, have the added benefit that they are unit-free (Brooks, 2014). The method used to calculate ‘returns’ from each time series was achieved as follows, in Equation (1):

$$r_t = ln\frac{y_t}{y_{t-1}} \qquad (1)$$

where y_i is the number of overnight stays at month i. So, we shall call variations in overnight stays as the 'returns' and, without losing generality, for the rest of this study, the interpretation of the word 'return' is made in the just explained sense. The seasonal patterns were first isolated from the original overnight stays' series using the Census X-12 decomposition method that is a widely used application. Basically, the method applies a series of sophisticated moving averages to estimate the seasonal factor, with additional calculations of the trend-cycle and irregular elements that capture effects that are unpredictable, including outliers and other irregular effects such as unseasonable weather, natural disasters and strikes (Ridderstaat, Oduber, et al., 2014).

In addition to the analysis of the descriptive statistics of the returns, we analysed the significance level of the correlations between the time series of the different markets. The interpretation of the correlation coefficient follows the classification: (i) weak or low correlation for $|r| \leq 0.35$, (ii) modest or moderate for $0.35 < |r| < 0.68$, (iii) high or strong correlation for $0.68 \leq |r| < 0.90$ and (iv) very high correlation for $|r| \geq 0.90$ (Taylor, 1990).

Subsequently, the preliminary analysis included the following panel unit root tests for stationarity: Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1981), Levin-Lin-Chu test (Levin, Lin, & James Chu, 2002), Im-Pesaran-Shin test (Im, Pesaran, & Shin, 2003) and Phillips-Perron (PP) test (Peter & Perron, 1988). Unit root test has become widely popular over the past several years because the regression of a nonstationary time series on another nonstationary time series may produce a spurious regression, so we need to check whether it is necessary to use cointegration to solve non-stationary problems. Cointegration analysis is used to test for the existence of a statistically significant connection between two, or more, time series by testing for the existence of a cointegrated combination of the two series (Agiomirgianakis et al., 2014; Gujarati & Porter, 2009).

We can say that, a time series, Granger causes another (unidirectional causality) if past values of the first significantly improve the prediction of the other, and one can say that there exists bidirectional causality when, simultaneously, past values of the second time series also improve significantly the prediction of the first series. If there is none of these relations between both time series, one can say that independency is suggested, assuming that both series are stationary. Nevertheless, the word 'causality' in this context should be seen as a misleading term because the Granger-causality means only a correlation between the current value of one time series and the past values of other, but it does not mean that movements of one cause movements of another (Brooks, 2014; Gujarati & Porter, 2009).

The most common method for the estimation, of classical linear regression model, is the Ordinary Least Squares (OLS) and may use, as explanatory variables, only the past values of the variable (lags) in study. Such models are Autoregressive Distributed Lag (ARDL) models and, in the context of this research, they can be specified with Equation (2) for l lags and the presence of past values can be a problem to the classical OLS because of the possibility of autocorrelation and the presence of non-stochastic variables (like lagged values). The existence of autocorrelation can be statistically verified using Breusch–Godfrey (BG) test that allows non-stochastic variables, such as the lagged values. The null hypothesis of this test is that there is no autocorrelation of any order, for l lags. For large samples $(n-l)R^2$ as a χ^2 distribution with l degrees of freedom (Gujarati & Porter, 2009).

$$r_t = C + \sum_{i=1}^{l} \beta_i r_{t-i} + u_t \tag{2}$$

In order to choose the appropriate ARDL model, i.e., the number of lags that should be used in the estimation, we can use a few criteria. Among the most common criteria to judge the adequacy of a regression model is the Akaike's Information Criterion (AIC) that uses the idea of imposing a penalty for adding regressors to the model. In comparing two or more models, the model with the lowest value of AIC, calculated from Equation (3), is preferred. In this equation, k is the number of regressors, including the interceptor and n is the number of observations (Gujarati & Porter, 2009).

$$AIC = e^{\frac{2k}{n}} \frac{\sum \hat{u}_i}{n} \tag{3}$$

The Lagrange Multiplier (LM) test is one of the more modern tests that detect autoregressive conditional heteroscedasticity in the residuals. The null hypothesis of this test is that there is no ARCH up to order l in the residuals, and the software EViews© (Standard Edition for Windows, Version 10) reports Engle's LM test statistic, that is asymptotically distributed as a $\chi^2_{(l)}$ (Wooldridge, 2012).

3.5. Forecasting Models

A time series is a set of observations relating to the values of a variable at different time points. This type of data can be collected regularly in time (daily, weekly, monthly, quarterly, annual, among others) or irregularly. Although this type of data is widely used in economic sciences, time series can present problems, since most empirical studies assume that they are stationary data, that is, that they do not vary in mean or variance throughout the time (Gujarati & Porter, 2009), when, in fact, they are nonstationary.

According to Poon (2005), volatility refers to the range of values that an uncertain variable can take. Volatility is often statistically measured through the variance or standard deviation. These statistical results are commonly associated with risk or uncertainty. The concept of volatility was, originally, typical of financial phenomena, but the fact that the tourism industry is very sensitive, occurring periods of ‘ups’ and ‘downs’ in the activity, can be characterized by a volatile behaviour.

Forecasting models can be linear in mean and variance or linear in mean, but non-linear in variance. Volatility, as measured by the standard deviation or variance of returns, is often used as a crude measure of the total risk of financial assets (Brooks, 2014). Volatility clustering is a phenomenon known by periods, in a time series, that exhibit wide swings for an extended time period, followed by a period of comparative tranquillity (Gujarati & Porter, 2009).

Traditional models assume that the variance of the structure of errors remains constant over time (homoscedasticity hypothesis) and, to generalize this improbable assumption, since economic time series may show periods of low volatility followed by periods of high volatility, and to solve questions related to risk and uncertainty in economic theory, there is a class of stochastic processes called ARCH processes that are mean zero, serially uncorrelated with non-constant conditional variances, but constant unconditional variances. For such processes, the recent past gives information about the forecasted variance assuming that the conditional variance depends on past volatility measured as a linear function of past squared values of the process (Engle, 1982).

In this research, besides the standard ARCH model, three extensions of the original model were used, namely the GARCH, Exponential Generalized Autoregressive Conditionally Heteroscedastic (EGARCH) and Threshold Generalized Autoregressive Conditionally

Heteroscedastic (TGARCH) models. The conditional variance provided by these estimates is used as a proxy for the volatility of overnight stays' returns' series.

The specification of the models in the context of this thesis will be done according to Equation (4), as the focus of this research is the risk associated with the variability in tourist's overnight stays and not the behaviour of tourism demand in cities:

$$r_t = \mu + \sigma_t \varepsilon_t \tag{4}$$

where r_t is defined by Equation (1), μ is the mean of the returns, σ_t^2 is the conditional variance and ε_t is a sequence of $\mathrm{N}(0,1)$ independent and identically distributed random variables. The residual return is defined in Equation (5).

$$u_t = r_t - \mu = \sigma_t \varepsilon_t \tag{5}$$

3.5.1. The Generalized Autoregressive Conditionally Heteroscedastic Model

The most popular non-linear financial models are the ARCH and GARCH models used for modelling volatility (Brooks, 2014; Menezes & Oliveira, 2015). The ARCH model was introduced by Engle (1982) and provides a framework for the analysis and development of time series models volatility. The specification of an ARCH(p) model is given by Equation (6).

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 \tag{6}$$

In this model $\omega > 0$ and $0 \leq \alpha_i < 1$ to ensure positive variance and covariance stationarity. As σ_t^2 is the conditional variance, it must always be strictly positive, because a negative variance at any point in time would be meaningless so, to guarantee that this model always originates positive conditional variance estimates, all of the coefficients in the conditional variance are required to be non-negative. However, the number of lags of the squared error that are required to capture all of the dependence in the conditional variance, might be very large, what would result in a large conditional variance model that is not parsimonious and may cause non-negativity constraints to be violated (Brooks, 2014).

To overcome these problems this model was generalized by Bollerslev (1986) to the GARCH model that is more parsimonious and avoids overfitting. The GARCH(p,q) is specified in Equation (7) but, in general, a GARCH(1,1) model, stated in Equation (8), will be sufficient to capture the data volatility and, rarely, is any higher order model estimated in the academic literature (Brooks, 2014).

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \quad (7)$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (8)$$

In this latter specification $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ because, on the contrary, the unconditional variance of u_t would not be defined. That is termed by non-stationarity in variance and does not have a strong theoretical motivation for its existence (Brooks, 2014).

For α and β coefficients, one of the following null hypotheses was tested through a Wald test: $\alpha = 1$ in the ARCH models and $\alpha + \beta = 1$ in the GARCH models. This test allows to statistically verify if there is finite memory in the models, namely, if there is a recovery time, since $\alpha + \beta$ is the persistence in these models (Dutta, 2014).

The ARCH and GARCH models assume that volatility is symmetric, that means that volatility would exhibit the same behaviour in the face of positive or negative shocks.

3.5.2. The Exponential Generalized Autoregressive Conditionally Heteroscedastic Model

The possibility that, in many markets, the impact of negative shocks causes greater volatility than the positive ones, has demonstrated the need for use of asymmetric volatility models, because the GARCH models assume that variance is determined only by magnitude and not by the positivity and negativity of unanticipated returns (Ferreira, Menezes, & Mendes, 2007). One model to account for this asymmetry is the EGARCH(*q*,*p*) model introduced by Nelson (1991) and it is specified in Equation (9) and, its reduced formulation EGARCH(1,1), in Equation (10).

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \left|\frac{u_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{p} \beta_i \ln \sigma_{t-i}^2 \quad (9)$$

$$\ln \sigma_t^2 = \omega + \alpha \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}} + \beta \ln \sigma_{t-1}^2 \quad (10)$$

This model has several advantages over the pure GARCH specification because one does not need to impose non-negativity constraints, once, even if the parameters are negative, σ_t^2 will be positive, and asymmetries between returns and volatilities are captured by the γ parameter. The statistical significance of $\gamma \neq 0$ explains the existence of asymmetry. The sign of this coefficient means that positive shocks will increase volatility and have a more persistent effect than negative shocks, when the coefficient is positive, and the opposite when γ is negative (negative shocks will increase volatility more than positive ones or leverage effect). The persistence of the effects can be evaluated through the β parameter (Brooks, 2014) and the magnitude of bad and good news can be evaluated by $1-\gamma$ and $1+\gamma$, respectively (Dutta, 2014).

The symmetric long-run covariance matrix using a non-parametric kernel estimator with a Bartlett kernel and a real-valued bandwidth (determined using the number of observations) can be displayed for panel time series and the results on matrix's diagonal could be compared with variance series' mean from the EGARCH models.

3.5.3. The Threshold Generalized Autoregressive Conditionally Heteroscedastic Model

Another model that takes into account the possibility of asymmetry in the volatility behaviour is the TGARCH model. The TGARCH model is a simple extension of a GARCH model introducing a term that would count for possible asymmetries and is specified in Equation (11) in the case of TGARCH(q,p) and in Equation (12) in its reduced formulation, TGARCH(1,1).

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \gamma_i u_{t-i}^2 I_{t-i} \tag{11}$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{12}$$

In these specifications $I_{t-i} = 1$ if $u_{t-i} < 0$ and $I_{t-i} = 0$, otherwise. The conditions for non-negativity are $\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \gamma \geq 0$ (Brooks, 2014).

In this model, asymmetric effects are captured by γ parameter, that measures the contribution of shocks to short-run persistence $\left(\alpha + \frac{\gamma}{2}\right)$ and to long-run persistence $\left(\alpha + \beta + \frac{\gamma}{2}\right)$ (C. L. Chang & McAleer, 2012). The sign of the γ coefficient means that positive shocks will increase volatility more than negative shocks when the coefficient is negative, and the opposite when γ is positive (negative shocks will increase volatility more than positive ones or leverage effect), that is the contrary of γ interpretation in the EGARCH models. The magnitude of good and bad news can be evaluated by α and $\alpha + \gamma$, respectively (Dutta, 2014).

For the α, β and γ coefficients, one of the following null hypotheses was tested through a Wald test: $\alpha + \frac{\gamma}{2} = 1$ in the models without the GARCH component, i.e. Threshold Autoregressive Conditionally Heteroscedastic (TARCH) models, and $\alpha + \beta + \frac{\gamma}{2} = 1$, in models with GARCH component. This test allows to statistically verify if there is finite memory in the models, namely, if there is a recovery time, since $\alpha + \beta + \frac{\gamma}{2}$ is the persistence in these models (Dutta, 2014).

3.5.4. Concluding Remarks

Autoregressive conditional heteroscedastic models are the most appropriate nonlinear theoretical models to model time series volatility. Thus, in order to test the accuracy of different models, according to the literature, the ARCH or GARCH models will be used to verify if the effects of good news on tourism demand volatility are similar to the effects of bad news or, on the contrary, the effects are different and the EGARCH or TGARCH models are the most adequate in volatility modelling.

These models will allow the evaluation of the persistence of shocks (positive or negative) on tourism demand volatility, as well as the magnitude of good and bad news, for each city and for each source market.

Other extensions of the original ARCH model could also be used but, in any case, some experiments were attempted without improving the results. Thus, for reasons of parsimony, we shall only rely on the estimates of the models here described.

4. Results and Discussion

4.1. Preliminary Data Analysis

For each of the source regions and for each city the seasonal patterns were first isolated from the original overnight stays' series using the Census X-12 decomposition method and sporadic or occasional events were revised, since the objective of this research is to analyse the behaviour of the variance and not the mean. These occasional events are defined as anomaly points where the behaviour of the time series is unusual and significantly different from previous or following data. An anomaly may signify a negative or a positive change but, either way, it categorises an abnormal behaviour (Ahmad, Lavin, Purdy, & Agha, 2017). According to Charles (2008) volatility forecasts are better when data are cleaned of outliers for several short, medium and long term forecasts.

After reviewing the anomaly values in the seasonally adjusted series with the overnight stays related to the different markets analysed, the seasonality components were observed, in order to identify the behaviour of the variance over time. Subsequently time series were built with the returns, which allowed a previously identification of the existence of moments of larger and slighter volatility. An analysis of the main descriptive measures of the time series of the returns under study was also carried out.

In this preliminary data analysis, correlations between overnight stays from each of the source markets were also calculated and evaluated, and the necessity of using cointegration was assessed through unit root tests. The Granger causality tests were also performed in all pairs of returns from overnight stays, as well as tests for autocorrelation and heteroscedasticity.

The possibility of existence of autocorrelation, was statistically verified using BG tests and the problem of the existence of heteroscedasticity was tested via heteroscedasticity LM tests.

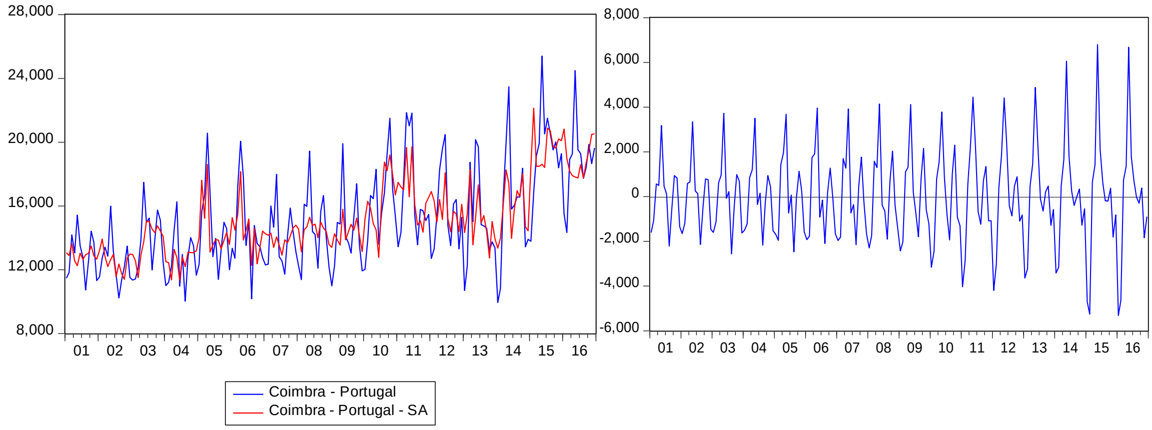
All estimation was conducted using EViews© (Standard Edition for Windows, Version 10).

4.1.1. Overnight Stays in Coimbra

In Coimbra, data on overnight stays from domestic tourism, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 10, which shows the non-existence of occasional events to be corrected.

Figure 10 - Overnight stays (a) and seasonality component (b) in Coimbra from Portugal

(a) (b)

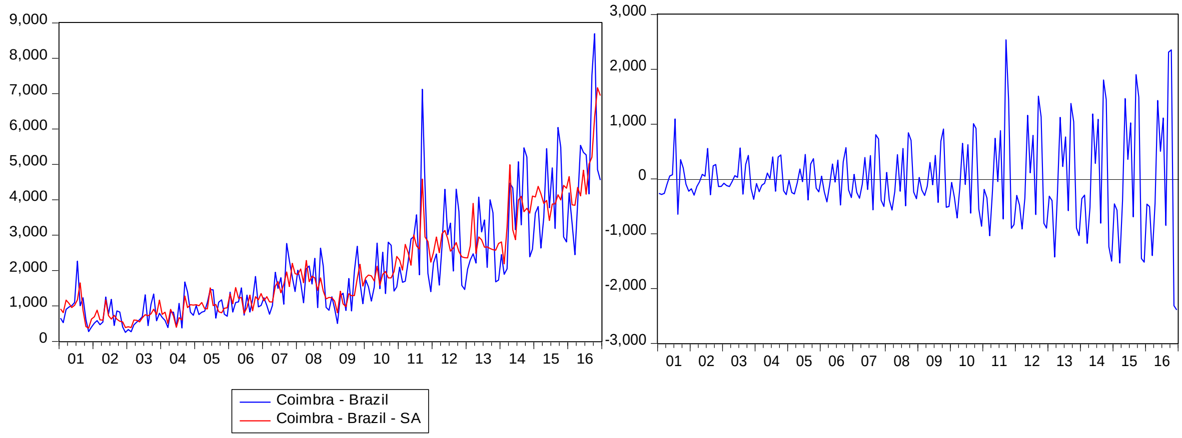


Source: author

Data on overnight stays from Brazil in Coimbra, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 11, which allowed the identification of an occasional event in September 2011. On September 8 and 9, 2011 took place in Coimbra an international seminar *Policies and Experiences in Energy Efficiency Portugal – Brazil* that was organized by the Institute for Systems Engineering and Computers at Coimbra and the Electricity Sector Study Group from the Federal University of Rio de Janeiro which may have contributed for this sporadic event. In this month also have occurred the 11th annual meeting of the European Network for Business and Industrial Statistics at the University of Coimbra. The results after correction of this value, before and after seasonality adjustment (a) and the final seasonality component (b) can be observed in Figure 12.

Figure 11 - Overnight stays (a) and seasonality component (b) in Coimbra from Brazil before event correction

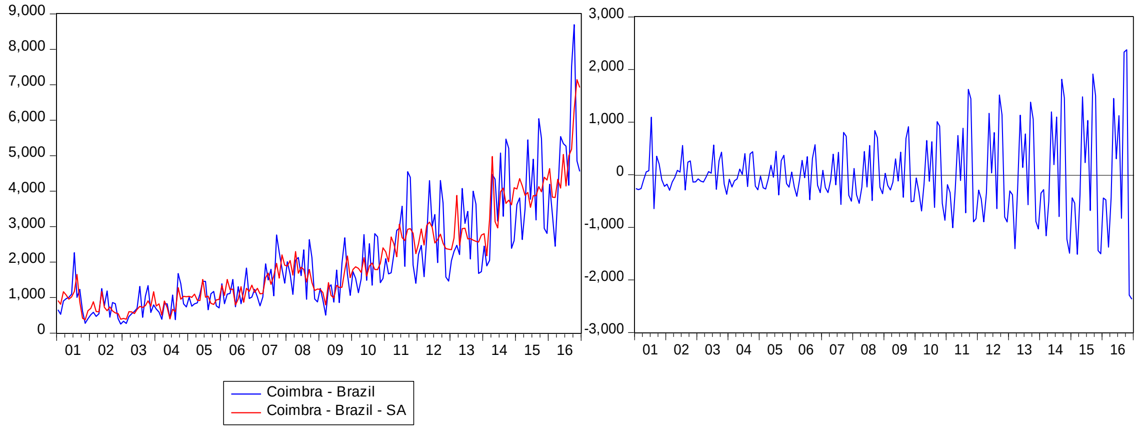
(a) (b)



Source: author

Figure 12 - Overnight stays (a) and seasonality component (b) in Coimbra from Brazil after event correction

(a) (b)

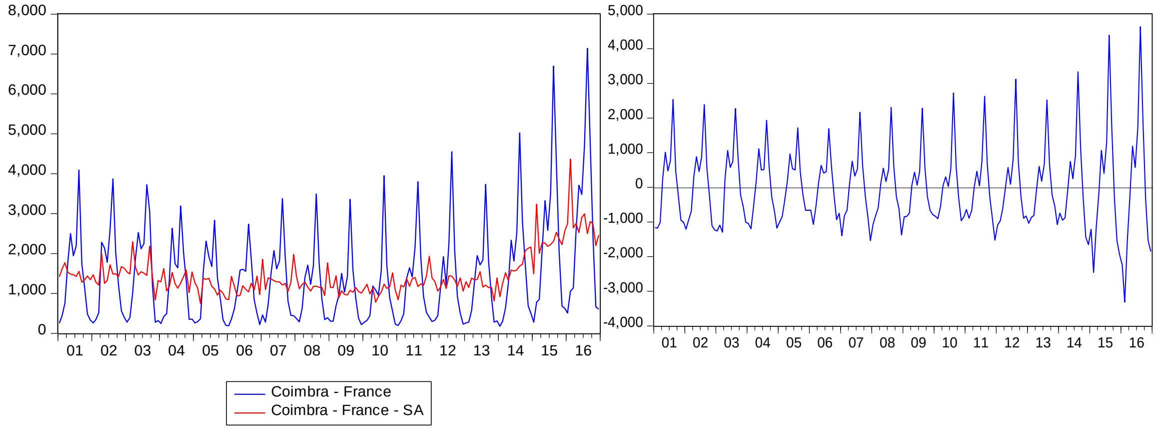


Source: author

Data on overnight stays from France in Coimbra, before and after seasonal adjustment (a), in combination with seasonality component (b) can be observed in Figure 13, which permitted to observe the non-existence of occasional events to be corrected.

Figure 13 - Overnight stays (a) and seasonality component (b) in Coimbra from France

(a) (b)

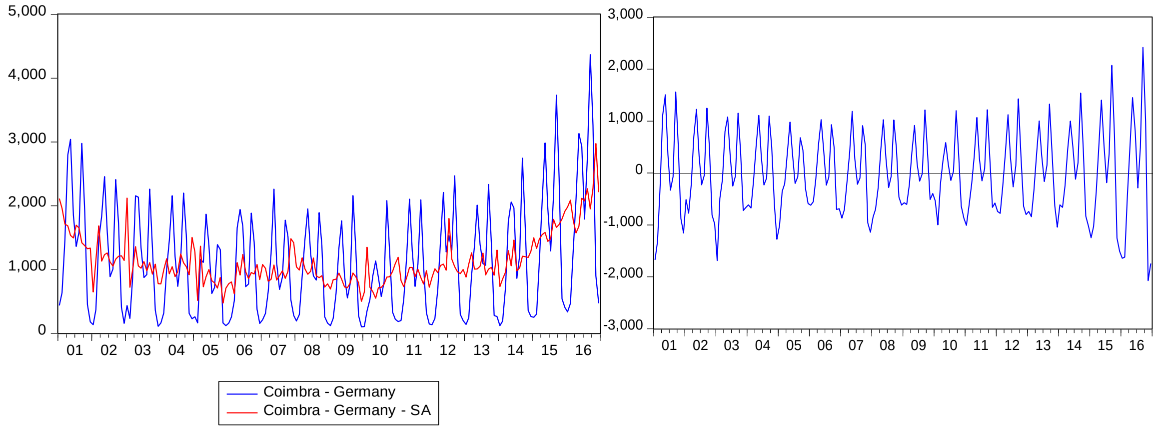


Source: author

Overnight stays from Germany in Coimbra before and after seasonal adjustment (a) and seasonality component (b) can be observed in Figure 14, what allowed the identification of a sporadic event in January 2003. Between January 20 and February 2, 2003 took place in Guimarães the 18th edition of the Men's World Handball Championship and Germany was one of the four main candidates for the final victory. The meteorological conditions in January 2003 in Germany were exceptionally characterized by historical floods (Beurton & Thieken, 2009; Brázdil et al., 2012), which may have caused a change in tourism demand on the part of this market. The results after the correction of this value, before and after seasonal adjustment (a) and seasonality component (b) can be observed in Figure 15.

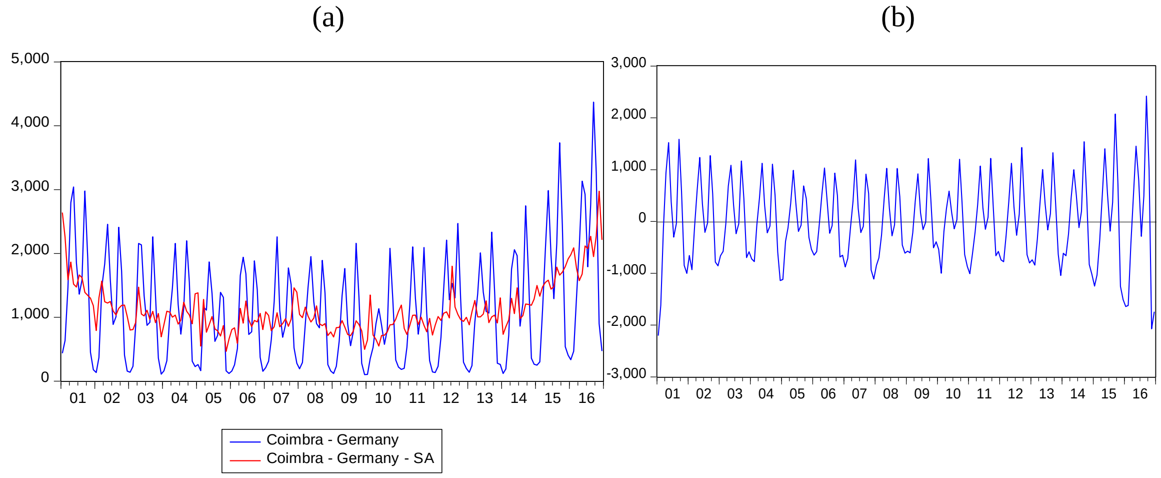
Figure 14 - Overnight stays (a) and seasonality component (b) in Coimbra from Germany before event correction

(a) (b)



Source: author

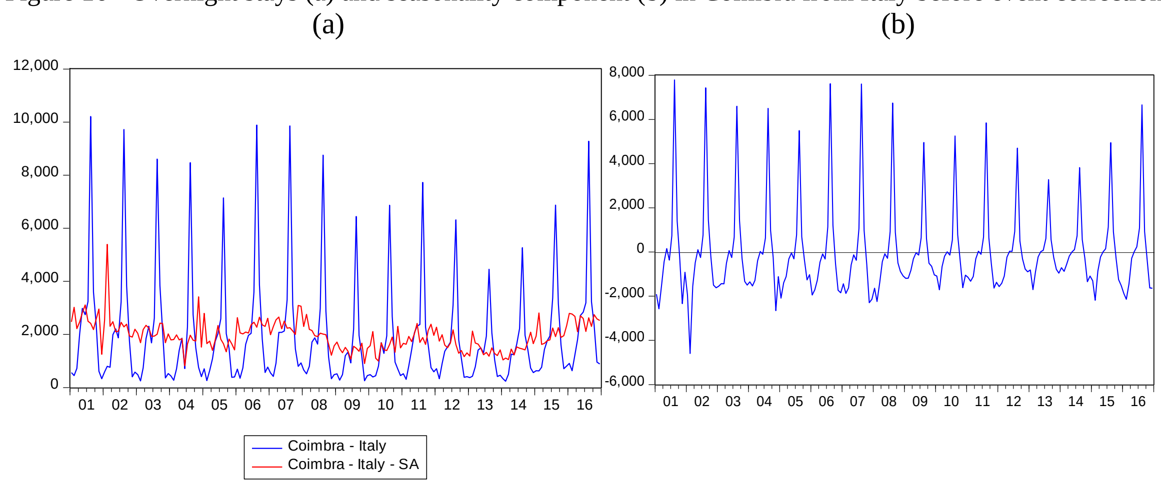
Figure 15 - Overnight stays (a) and seasonality component (b) in Coimbra from Germany after event correction



Source: author

Data on overnight stays from Italy, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 16. These permitted the observation of an anomalous occurrence in February 2002. In 2002, an advertising campaign was ongoing, where it was heralded Portugal as 'Warm by the Nature' (Ramalho, 2013). In Figure 17 we can observe the results after the modification of this value, before and after seasonality adjustment (a) and the final seasonality component (b).

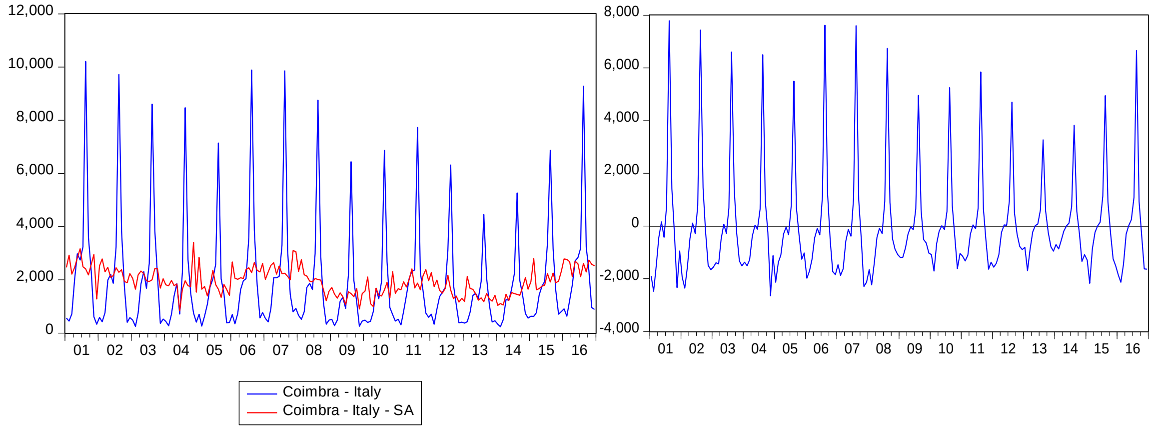
Figure 16 - Overnight stays (a) and seasonality component (b) in Coimbra from Italy before event correction



Source: author

Figure 17 - Overnight stays (a) and seasonality component (b) in Coimbra from Italy after event correction

(a) (b)

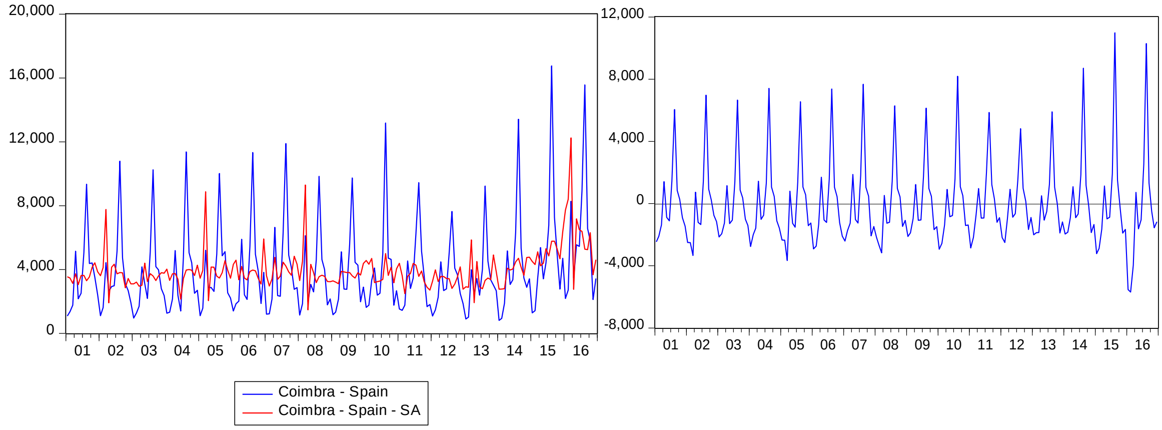


Source: author

Overnight stays from Spain in Coimbra, before and after seasonal adjustment (a) combined with seasonality component (b) can be observed in Figure 18 which allowed to notice the non-existence of occasional events to be corrected.

Figure 18 - Overnight stays (a) and seasonality component (b) in Coimbra from Spain

(a) (b)



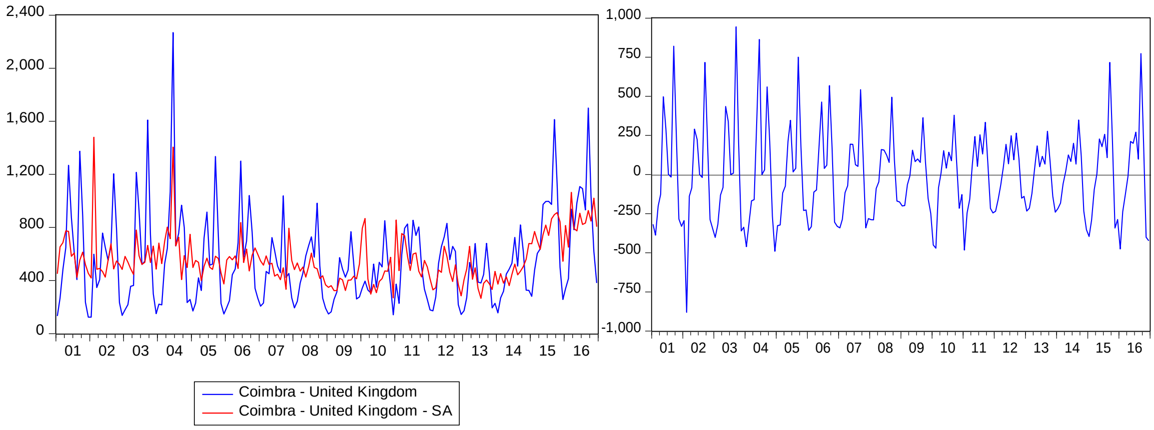
Source: author

From the United Kingdom, in Coimbra, overnight stays, before and after seasonal adjustment (a) conjugated with seasonality component (b), can be saw in Figure 19, which allowed the identification of a sporadic event in February 2002. As it was said in the analysis of overnight stays from Italy, in 2002, an advertising campaign was held for some of the main markets, particularly for the United Kingdom market, that could be responsible for this sporadic event

(Ramalho, 2013). Figure 20 shows the results after the correction of this value, before and after seasonal adjustment (a) and the respective seasonality component (b).

Figure 19 - Overnight stays (a) and seasonality component (b) in Coimbra from the United Kingdom before event correction

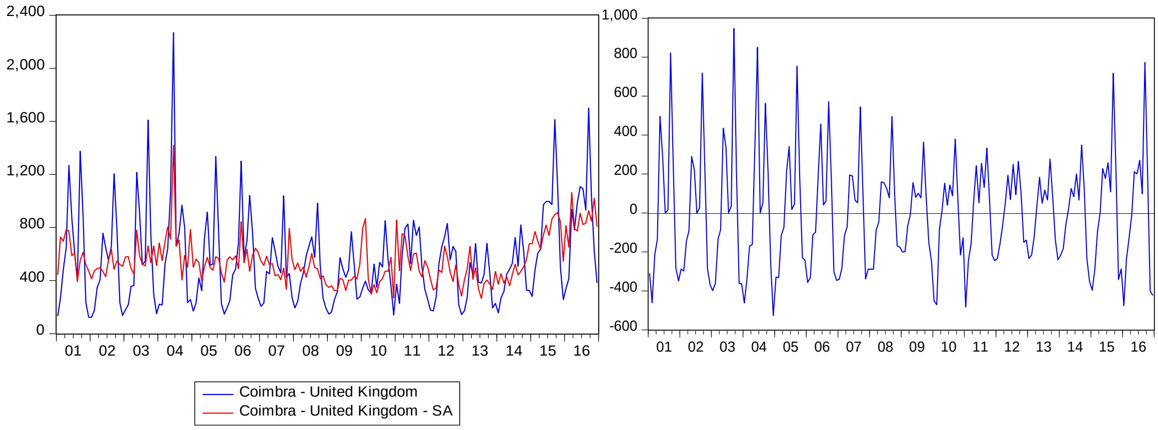
(a) (b)



Source: author

Figure 20 - Overnight stays (a) and seasonality component (b) in Coimbra from the United Kingdom after event correction

(a) (b)

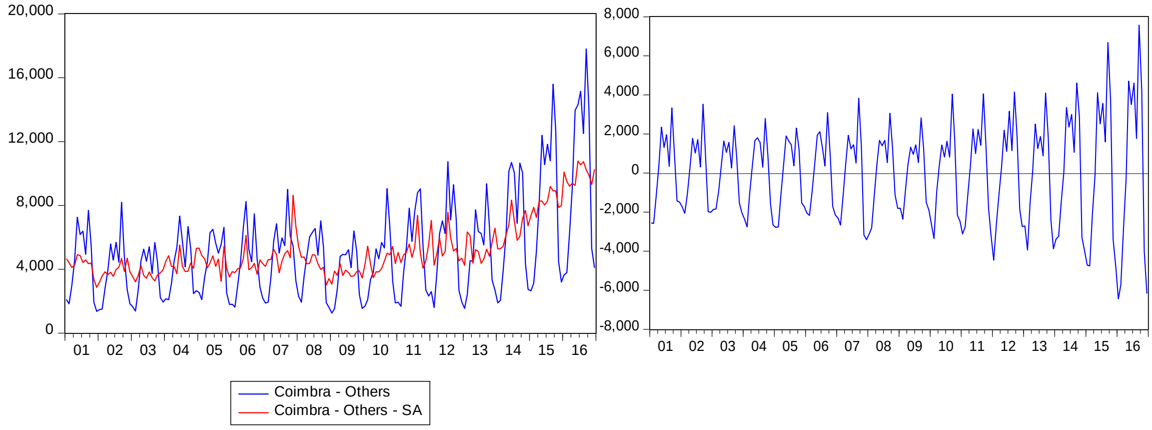


Source: author

With regard to overnight stays from other countries not specified in this research work in Coimbra, the chart with data and data seasonally adjusted (a), as well as the seasonal component (b) can be seen in Figure 21, where we can verify the absence of the need for correction of sporadic events in the time series.

Figure 21 - Overnight stays (a) and seasonality component (b) in Coimbra from non-specified countries

(a) (b)

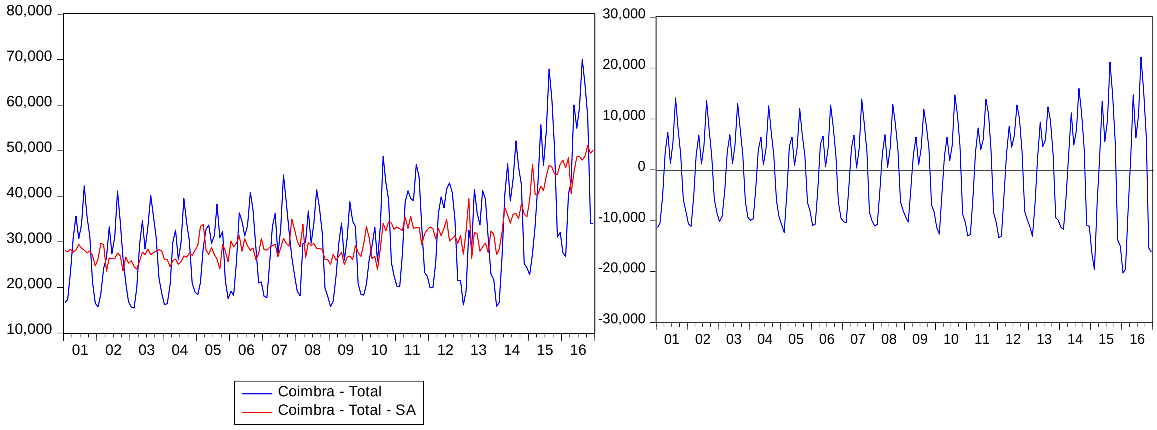


Source: author

Finally, with regard to the total overnights in Coimbra, the chart of data and data with seasonal adjustment (a), as well as the seasonality component (b), can be observed in Figure 22, where, once again, we can verify the non-existence of irregular events in the time series.

Figure 22 - Total overnight stays (a) and seasonality component (b) in Coimbra

(a) (b)

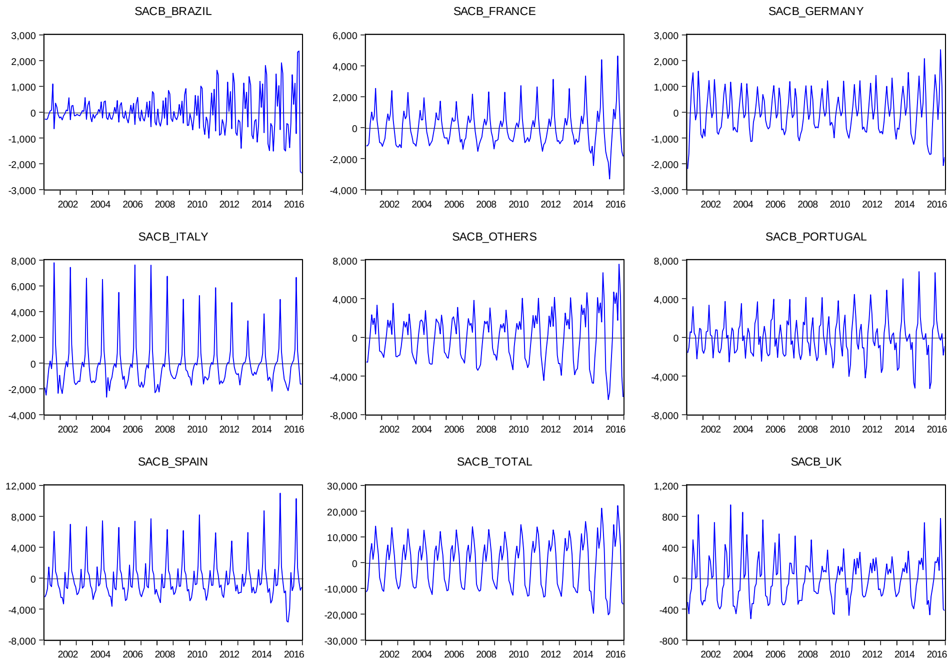


Source: author

All the time series of overnight stays in Coimbra express an increasing tendency with greater slope from the year 2014 forward.

Figure 23 shows the seasonal components of the time series with seasonal adjustment related to overnight stays in Coimbra. We can observe the existence of growing variance in time series from Brazil, France, Germany, Italy, Spain and the United Kingdom (the last three, after a period of constant or decreasing variance). This kind of behaviour (increasing variance) can also be observed in overnight stays from domestic tourism, other non-specified countries and also for the total overnight stays (this one after a large period of constant variance).

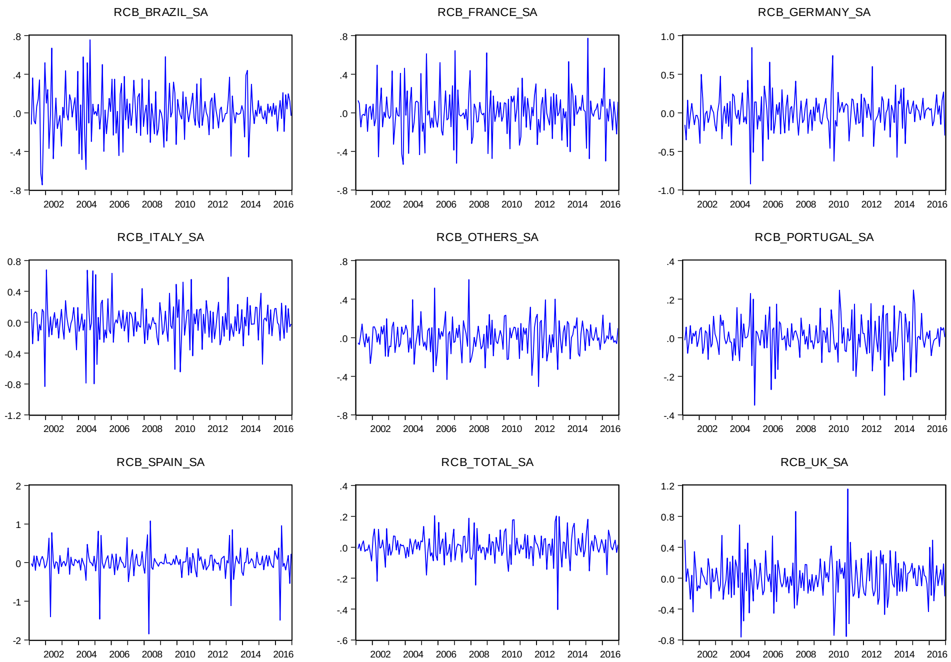
Figure 23 - Seasonality components after seasonal adjustment for overnight stays in Coimbra



Source: author

After the conversion of the seasonal adjusted series with overnight stays in Coimbra for series of returns, we can observe, for all the inbound markets, moments of greater volatility - denser zones - based on Figure 24 in particular with the series of returns from Brazil, France, Italy and the United Kingdom.

Figure 24 - Time series of returns of overnight stays in Coimbra



Source: author

The descriptive statistics of the returns of overnight stays in Coimbra can be observed in Table 10. It can be seen that the returns with the highest mean are those of overnight stays from Brazil, the lowest positive mean occurs with Italy and the only country that presents returns with negative mean is Germany. However, 50% of the returns are negative for overnight stays coming from Portugal, Brazil, France, Italy and the United Kingdom.

The largest return was 115% for the United Kingdom and the lowest return was -184% for Spain. The coefficient of variation is quite high in all source markets, which indicates a large relative dispersion of data and little representativeness of the mean.

In the analysis of skewness, the returns from overnight stays from Portugal, Germany, Italy, Spain and total overnight stays have negative asymmetry, that is to say, distributions have elongated left tails. All distributions are leptokurtic.

The Jarque-Bera statistic allows us to test the null hypothesis of a time series with a normal distribution, and in this analysis, we opt for the rejection of this hypothesis for all regions of origin at the usual levels of significance (Appendix A).

Table 10 - Descriptive statistics of the returns of overnight stays in Coimbra from markets analysed

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Mean	0.002364	0.010582	0.002887	-0.000923	0.000119	0.001382	0.003128	0.004136	0.003045
Median	-0.002997	-0.002367	-0.004813	0.005268	-0.014509	0,000023	-0.004013	0.006004	0.000366
Maximum	0.247107	0.754814	0.772404	0.844881	0.678522	1.078821	1.153871	0.602806	0.204397
Minimum	-0.350034	-0.746935	-0.535421	-0.922011	-0.834079	-1.844632	-0.764290	-0.506366	-0.404218
Std. Dev.	0.096354	0.237659	0.230641	0.233956	0.248254	0.348492	0.264508	0.162017	0.085637
Coef. of Var.	40.76	22.46	79.89	-253.47	2086.17	252.16	84.56	39.17	28.12
Skewness	-0.334027	0.066720	0.271583	-0.052659	-0.152216	-1.477458	0.344213	0.104057	-0.479054
Kurtosis	4.112701	3.887218	3.838122	5.201298	4.706908	11.40695	5.152438	4.251943	5.438894
Jarque-Bera	13.41***	6.41**	7.94***	38.65***	23.92***	631.96***	40.64***	12.82***	54.64***
Sum	0.451503	2.021096	0.551476	-0.176294	0.022748	0.263874	0.597370	0.790071	0.581512
Sum sq. Dev.	1.763965	10.73153	10.10715	10.39974	11.70973	23.07489	13.29323	4.987433	1.393387

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

Table 11 shows the correlations (Appendix B) between overnight returns from each of the source markets and allows us to conclude that the time series of returns of total overnight stays in Coimbra is statistically positively correlated (moderately) with the series of returns of overnights stays from Portugal, Spain, and non-specified countries and low correlated with Brazil, Germany, Italy and the United Kingdom according to Taylor's classification (1990). The correlation of this time series is not statistically significant just with the series of returns from overnight stays coming from France.

Returns from overnight stays from Germany in Coimbra are statistically positively correlated (low) with the time series from Italy, Spain and the United Kingdom and moderately with Others. The latter are also statistically positively correlated (moderately) with those from the United Kingdom and low with Italy. Those from France are statistically negatively correlated (low) with time series from Spain and the time series of returns from overnight stays from Portugal in Coimbra is statistically positively correlated (low) with the series of returns from overnight stays from Brazil.

Table 11 - Correlations between returns of overnight stays in Coimbra from different markets

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
Portugal	1.000000								
Brazil	0.223770***	1.000000							
France	0.083143	-0.075345	1.000000						
Germany	-0.035364	0.021477	0.033994	1.000000					
Italy	0.076742	0.137096	0.048445	0.195512***	1.000000				
Spain	0.065766	0.040247	-0.220400***	0.196949***	0.086102	1.000000			
UK	0.023504	-0.091911	-0.003616	0.177222**	0.063376	0.107786	1.000000		
Others	0.059837	0.018782	0.100497	0.400432***	0.239222***	0.100389	0.406431***	1.000000	
Total	0.624446***	0.235783***	0.031130	0.278353***	0.287152***	0.596710***	0.271764***	0.487495***	1.000000

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

The unit root test was performed with all the series of the returns simultaneously (Appendix C) for Coimbra and the hypothesis of non-stationarity was rejected at the usual levels of significance (Table 12).

Table 12 - Summary for group unit root test for returns from Coimbra

Method	Statistic	Probability
Levin, Lin & Chu t	-34.0627	0.0000
Im, Pesaran and Shin W-stat	-40.7867	0.0000
ADF - Fisher Chi-square	869.325	0.0000
PP - Fisher Chi-square	220.844	0.0000

Source: author

Then, the ADF tests were carried out for each of the individual series that confirmed the fact that it is not necessary to use cointegration, also at the usual levels of significance (Table 13).

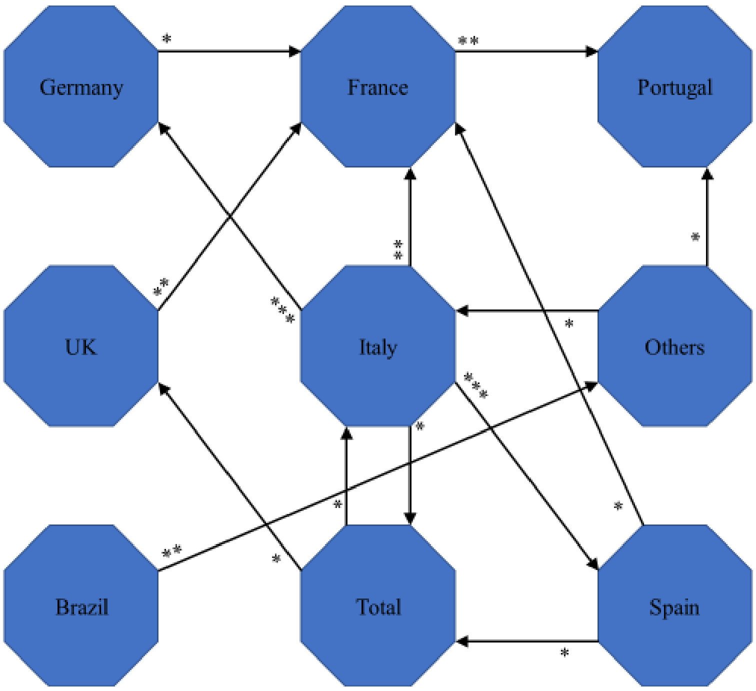
Table 13 - Summary of individual ADF tests for returns from Coimbra

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
ADF	-11.33***	-14.24***	-13.63***	-12.80***	-12.72***	-15.10***	-11.69***	-11.94***	-16.37***

Note: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

According to the Granger causality tests, we can observe that, for the series of returns of overnight stays in Coimbra, variations in the series with data coming from Brazil seem to cause changes in the time series with returns from non-specified countries, variations in the series from France seem to affect the series from Portugal, variations in the series from Italy seem to affect the series with the returns of overnight stays from France, Germany and Spain, and, finally, variations in the United Kingdom returns seem to affect series of returns from France. There are no bidirectional causalities. This analysis was performed according to the significance level of 5% (Appendix D). Taking into account the different usual levels of significance, the following Granger causalities can be observed in Figure 25.

Figure 25 - Granger causalities for all source markets in Coimbra



Note: *** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level

Source: author

Models were estimated for each source market using OLS and ARDL (Appendix E) specification and the possibility of existence of autocorrelation, was statistically verified using BG tests. The results can be seen in Table 14. It can be rejected that there is no autocorrelation of any order for all source markets for models without lags, but the problem of autocorrelation seems to be solved when lags are used, except for returns of overnight stays in Coimbra from Portugal.

Table 14 - Statistics for BG tests for OLS and ARDL (with number of lags) models for returns in Coimbra

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
OLS	34.87***	33.63***	62.60***	46.31***	59.20***	88.12***	44.77***	32.85***	44.76***
ARDL	11.69***	2.53	1.90	2.25	0.13	0.10	1.82	1.90	0.40
Number of lags	6	3	4	4	6	7	6	6	4

Note: *** denotes significance at 1% level; Others are non-specified countries.

Source: author

The fact that the usage of lags did not solve autocorrelation problem justifies, besides the heteroscedasticity problems, as it happened with returns from domestic market, the application of autoregressive conditionally heteroscedastic models.

The results of the heteroscedasticity LM tests are presented in Table 15, where we can conclude that we can reject the null hypothesis of non-existence of ARCH up to order l in the models without lags. The problem of the existence of heteroscedasticity is solved with the use of the ARDL specification for some markets but, for the returns from overnight stays in Coimbra, from Portugal, Brazil, Spain, the United Kingdom, non-specified countries and from total overnight stays, heteroscedasticity problem persists.

Table 15 - LM tests statistics for OLS and ARDL models for returns in Coimbra

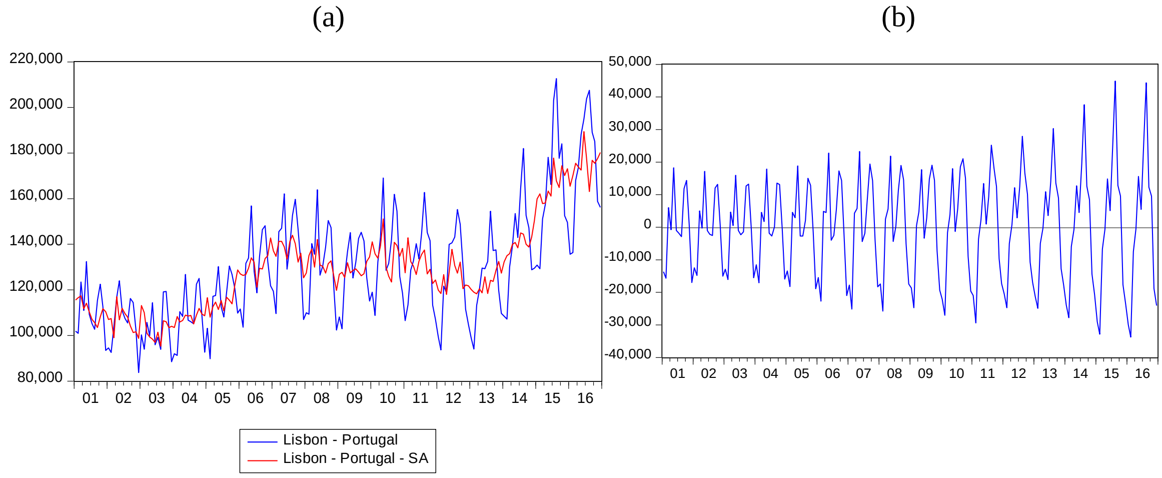
	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
OLS	14.09***	15.94***	30.12***	32.98***	28.50***	31.30***	28.06***	8.90***	17.98***
ARDL	6.95***	10.57***	0.32	0.02	0.03	30.80***	7.58***	0.74	5.88**

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

4.1.2. Overnight Stays in Lisbon

In Lisbon, data on overnight stays from domestic tourism, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 26, which shows the non-existence of occasional events to be revised.

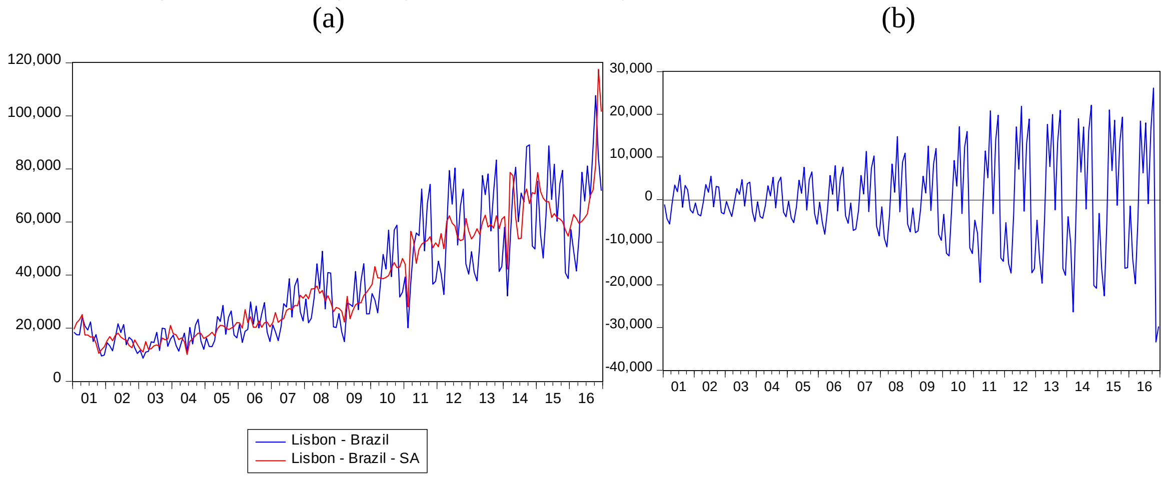
Figure 26 - Overnight stays (a) and seasonality component (b) in Lisbon from Portugal



Source: author

With regard to overnight stays, in Lisbon, from Brazil, the chart of data and data with seasonal adjustment (a), as well as the seasonality component (b), can be observed in Figure 27, where we can verify, also, the non-existence of irregular events in the time series.

Figure 27 - Overnight stays (a) and seasonality component (b) in Lisbon from Brazil

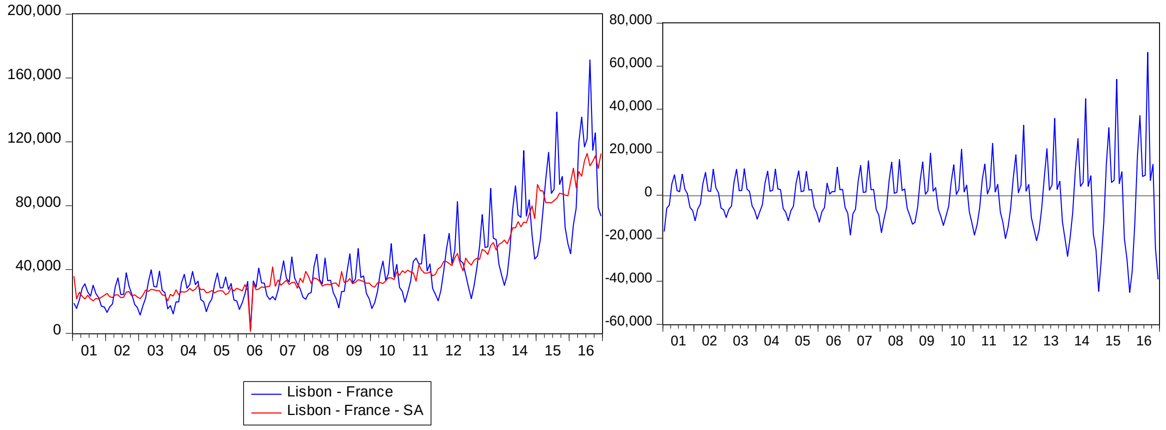


Source: author

Data on overnight stays from France, in Lisbon, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 28, which allowed the identification of an occasional event in May 2006. In this month, in Portugal, took place the final of the group stage of the UEFA Under 21 Championship between France and Portugal. The results after the correction of this value, before and after seasonality adjustment (a) and the final seasonality component (b) can be observed in Figure 29. It was, also, in this year that was carried out by Turismo de Portugal the advertising campaign ‘Portugal. A Deeper experience’ (Ramalho, 2013).

Figure 28 - Overnight stays (a) and seasonality component (b) in Lisbon from France before event correction

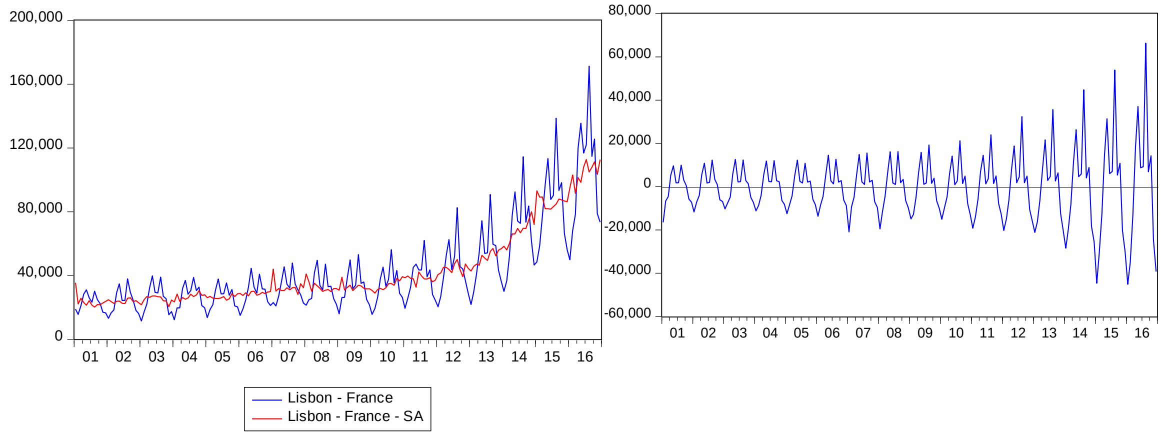
(a) (b)



Source: author

Figure 29 - Overnight stays (a) and seasonality component (b) in Lisbon from France after event correction

(a) (b)

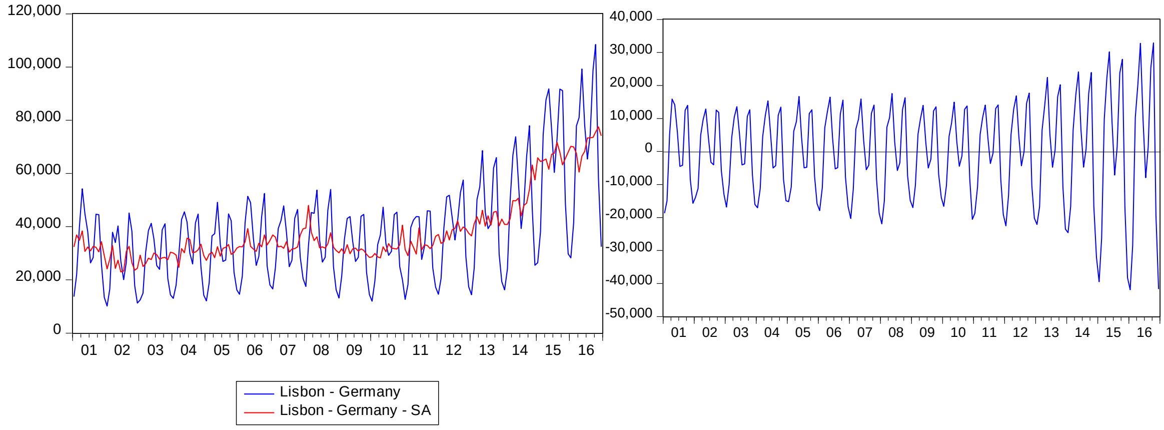


Source: author

Data on overnight stays from Germany in Lisbon, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 30 which allowed to observe the non-existence of sporadic events to be modified.

Figure 30 - Overnight stays (a) and seasonality component (b) in Lisbon from Germany

(a) (b)

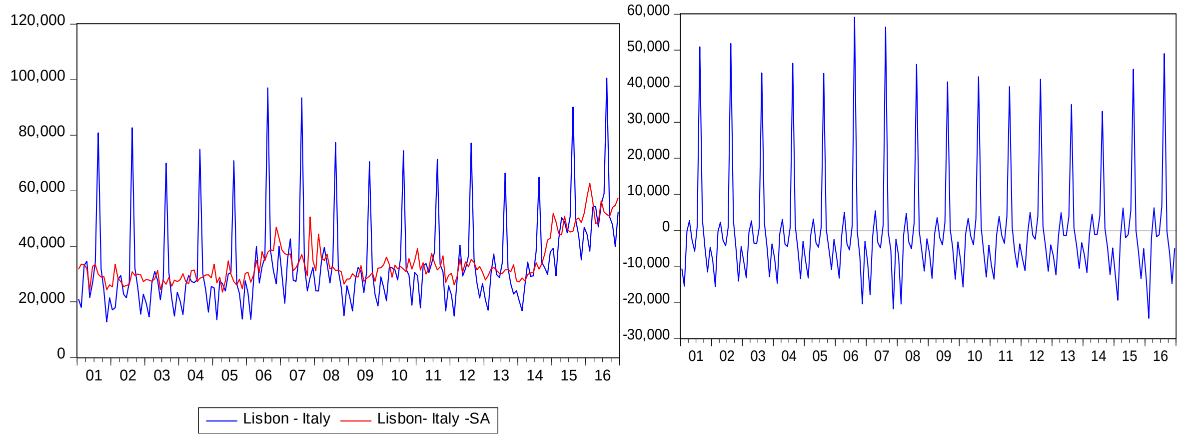


Source: author

Also, the time series with tourists' overnight stays from Italy (Figure 31) and from Spain (Figure 32), in Lisbon, before and after the seasonal adjustment (a) in combination with the seasonality component (b), show the non-occurrence of sporadic events to be corrected.

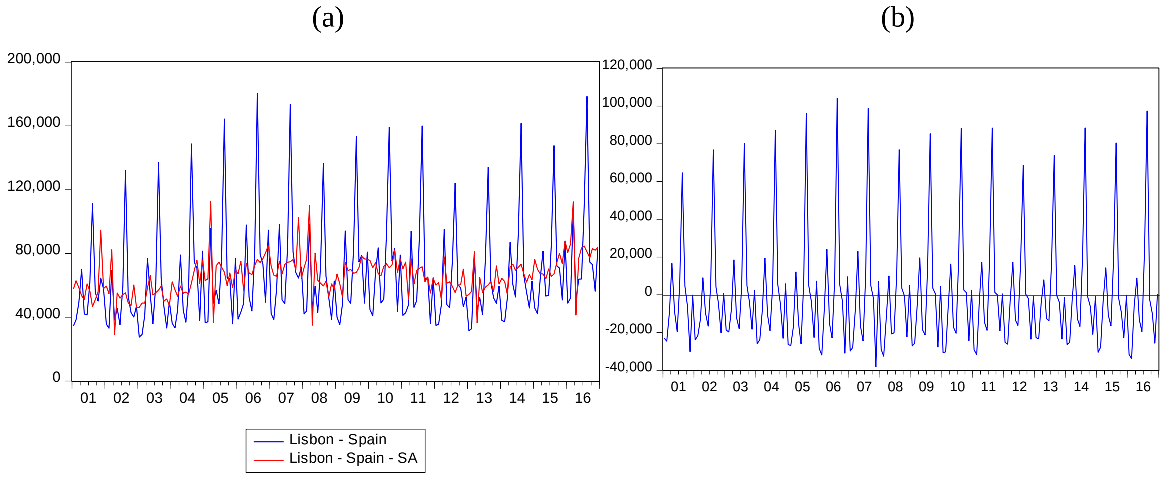
Figure 31 - Overnight stays (a) and seasonality component (b) in Lisbon from Italy

(a) (b)



Source: author

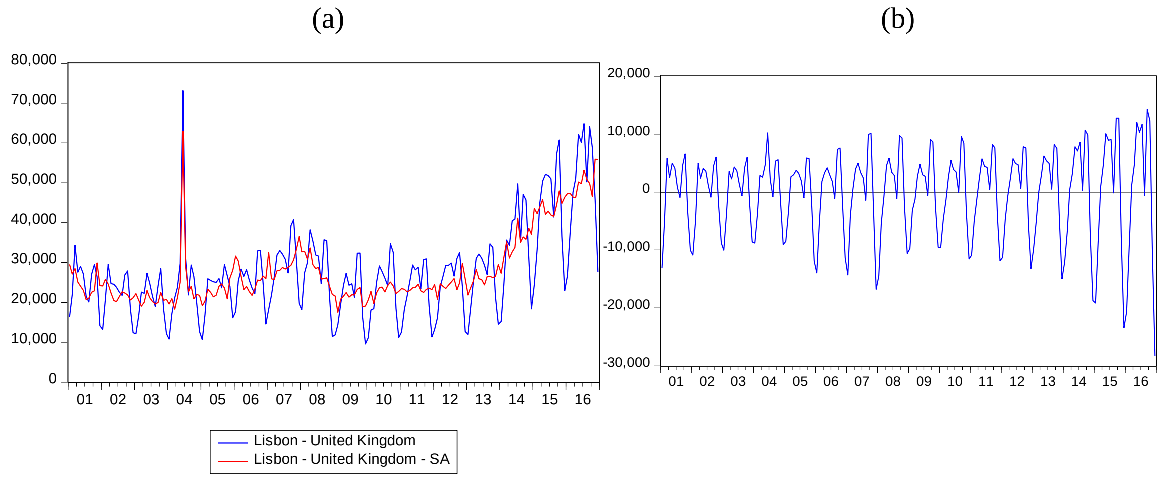
Figure 32 - Overnight stays (a) and seasonality component (b) in Lisbon from Spain



Source: author

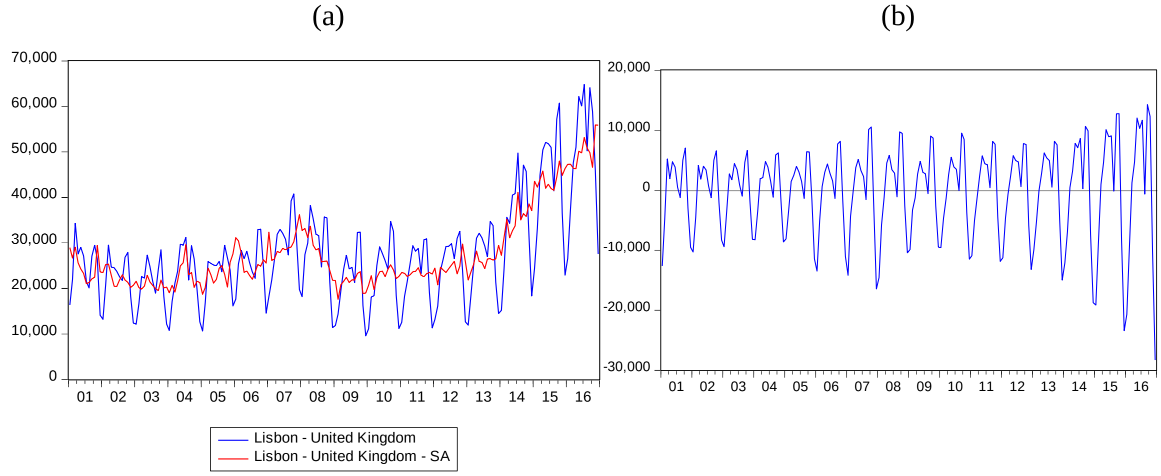
Overnight stays from the United Kingdom, in Lisbon, before and after seasonal adjustment (a) and seasonality component (b), can be observed in Figure 33, what allowed the identification of a sporadic event in June 2004. The 12th edition of the European Football Championship, known as Euro 2004, took place in Portugal between June 12 and July 4, 2004. The results after the correction of this value, before and after seasonal adjustment (a) and seasonality component (b) can be observed in Figure 34.

Figure 33 - Overnight stays (a) and seasonality component (b) in Lisbon from United Kingdom before event correction



Source: author

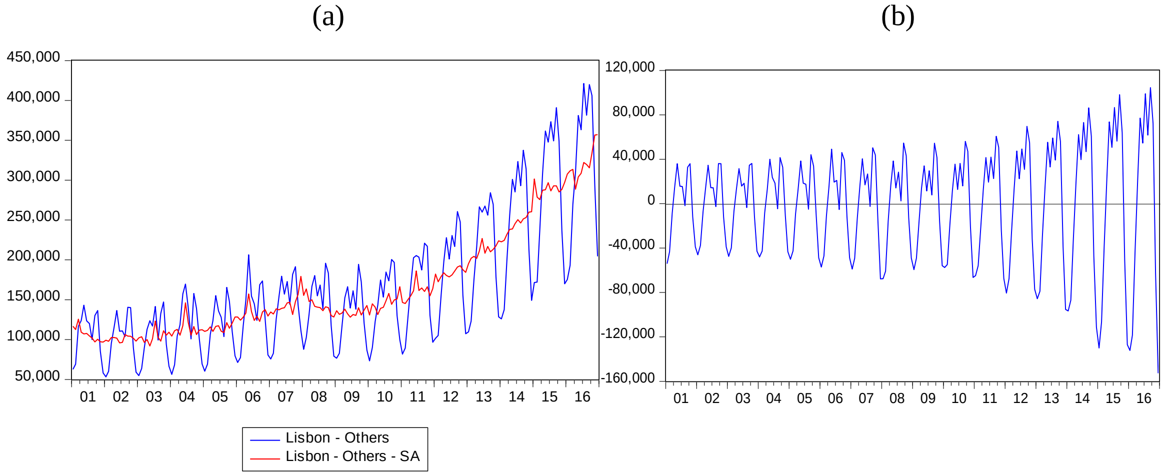
Figure 34 - Overnight stays (a) and seasonality component (b) in Lisbon from United Kingdom after event correction



Source: author

With respect to overnight stays from other countries, not specified in this research work, in Lisbon, the chart of the data and of data seasonally adjusted (a), as well as the seasonal component (b) can be seen in Figure 35, where we can verify the absence of the need for correction of sporadic events in the time series.

Figure 35 - Overnight stays (a) and seasonality component (b) in Lisbon from non-specified countries

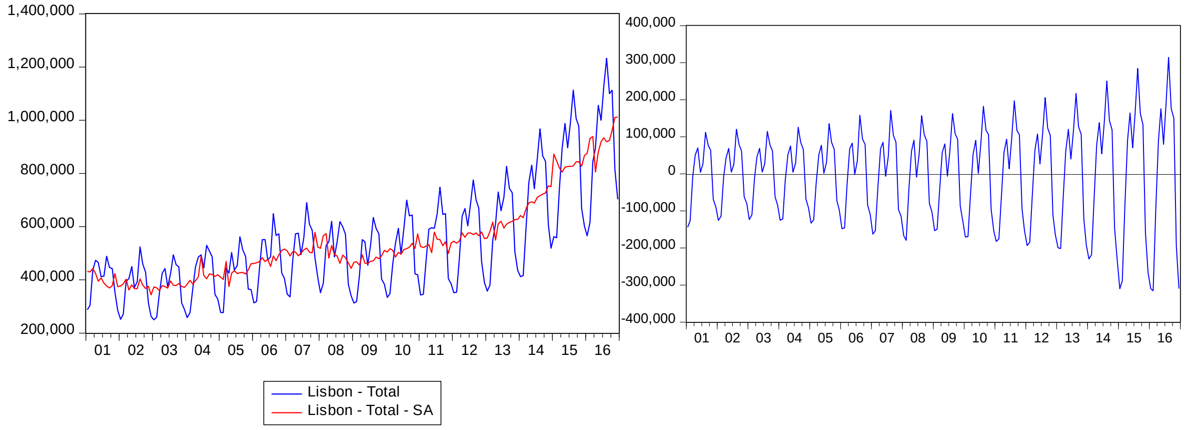


Source: author

Finally, with regard to the total overnights in Lisbon, the data and data with seasonal adjustment (a), as well as the seasonality component (b), can be observed in Figure 36, where, once again, we can verify the non-existence of irregular events in the time series.

Figure 36 - Total overnight stays (a) and seasonality component (b) in Lisbon

(a) (b)

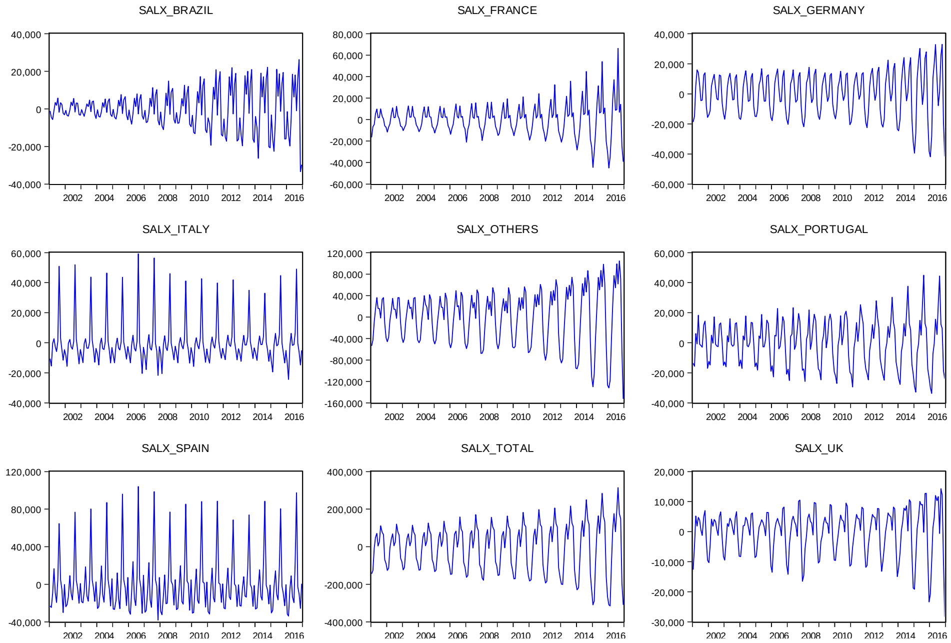


Source: author

As in Coimbra, all the time series with overnight stays in Lisbon show an increasing trend with higher slope from the year 2014 forward.

Seasonal components of the seasonally adjusted time series relative to overnight stays in Lisbon (Figure 37) show the existence of an increasing variance in the time series from Brazil, France, Germany and the United Kingdom (the last one after a period of decreasing variance). This type of behaviour can also be observed in overnight stays from domestic tourism (but less accentuated), other non-specified countries and also for total overnight stays. As regards to overnight stays from Italy and Spain, the variance has an approximately constant behaviour.

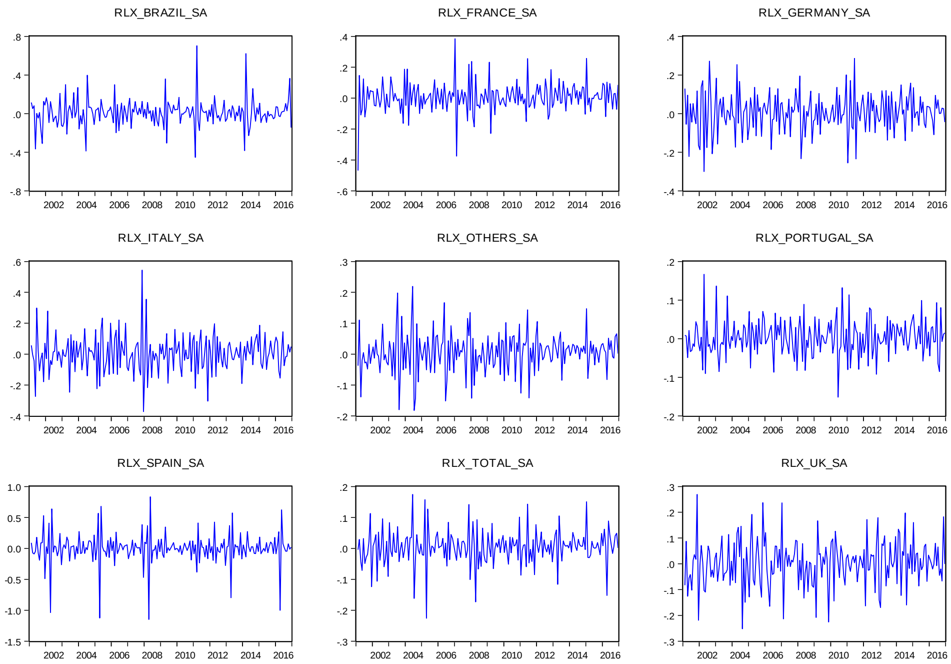
Figure 37 - Seasonality components after seasonal adjustment for overnight stays in Lisbon



Source: author

The seasonally adjusted time series with overnight stays in Lisbon were converted to series of returns, which allowed to identify the existence, for all source markets, of periods of more volatility in the observed time window (Figure 38), with a greater emphasis on Germany, Italy, Portugal and other non-specified countries.

Figure 38 - Time series of returns of overnight stays in Lisbon



Source: author

Table 16 shows the descriptive statistics of the returns from overnight stays in Lisbon. It can be seen that the returns with the highest mean are, as in Coimbra, those of the overnight stays coming from Brazil, and the lowest mean occurs with data from Spain. Contrasting with Coimbra there are no countries with negative returns average.

50% of returns are positive for overnight stays from all sources except for domestic tourism returns. The coefficient of variation is quite high in all markets, which indicates a large relative dispersion of the data and little representation of the mean, as it happened in the city of Coimbra.

In the analysis of asymmetry, the returns of overnight stays from France, Germany, Spain, the United Kingdom, non-specified countries and the total ones, show negative asymmetry, that is, distributions with elongated left tails. All distributions are leptokurtic.

The Jarque-Bera statistic allows the rejection of the null hypothesis of a time series with a normal distribution for all source markets at the usual levels of significance except for returns from overnight stays from Germany and the United Kingdom (Appendix A).

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Table 16 - Descriptive statistics of the returns of overnight stays in Lisbon from markets analysed

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
Mean	0.002329	0.008606	0.006056	0.004335	0.003112	0.001967	0.003437	0.005851	0.004458
Median	-0.002478	0.012701	0.001891	0.007610	0.005256	0.015000	0.006658	0.008499	0.005608
Maximum	0.166577	0.702187	0.383848	0.285753	0.543777	0.831413	0.269028	0.219131	0.174418
Minimum	-0.151275	-0.454539	-0.468619	-0.300363	-0.371932	-1.149973	-0.252369	-0.182402	-0.225613
Std. Dev.	0.047207	0.139406	0.096401	0.098782	0.118493	0.251155	0.089113	0.063615	0.055261
Coef. of Var.	20.27	16.20	15.92	22.79	38.08	127.68	25.93	10.87	12.40
Skewness	0.244198	0.791748	-0.366887	-0.189441	0.340198	-1.202941	-0.046164	-0.066376	-0.328412
Kurtosis	3.846679	8.567874	7.655197	3.491541	5.237419	10.10103	3.574608	4.202113	5.657079
Jarque-Bera	7.60**	266.67***	176.75***	3.07	43.52***	447.36***	2.70	11.64***	59.62***
Sum	0.444808	1.643702	1.156633	0.827992	0.594443	0.375778	0.656384	1.117449	0.851508
Sum Sq. Dev.	0.423415	3.692470	1.765685	1.854014	2.667694	11.98501	1.508807	0.768903	0.580226

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

According to Table 17 and Taylor's classification (1990), the time series of returns from overnight stays from Germany, in Lisbon, is statistically positively correlated (low) with those from Brazil, France, Italy, Spain, the United Kingdom and non-specified countries and moderately with total overnight stays. Only the correlation with Portugal returns is not statistically significant (Appendix B).

Returns of total overnight stays, in Lisbon, are statistically positively correlated (low) with the series of returns of overnight stays from Portugal, France and the United Kingdom, highly with Spain and moderately with Italy and non-specified countries. The latter are also statistically positively correlated (low) with those from France, Italy and the United Kingdom and those from Italy are statistically positively correlated (low) with time series from Portugal, France and Spain. Finally, the time series of returns from overnight stays from France, in Lisbon, is statistically positively correlated (low) with the series of returns from overnight stays from the United Kingdom.

Regardless of the intensity of the correlation, there are differences between what was observed with the returns from Coimbra and Lisbon. In Coimbra, returns from overnight stays from France were only statistically correlated with returns from Spain, which does not occur in Lisbon, where they are correlated with returns from Germany, Italy, the United Kingdom, non-specified countries and total overnight stays.

Brazilian returns from overnight stays, in Coimbra, were only correlated with returns from Portugal and total overnight stays, a fact that does not occur in Lisbon, where this market is statistically correlated with the German market. There are also differences between the Spanish market in the two cities: in Coimbra it is statistically correlated with returns from France (which is not the case in Lisbon) and in Lisbon is statistically correlated with that of Italy (which is not the case in Coimbra). This latter market, also, has differences in Lisbon, where it is statistically correlated with returns from domestic tourism, which does not occur in Coimbra.

Table 17 - Correlations between returns of overnight stays in Lisbon from different markets

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
Portugal	1.000000								
Brazil	-0.032364	1.000000							
France	0.026960	0.097395	1.000000						
Germany	-0.059352	0.186790***	0.144320**	1.000000					
Italy	0.205827***	0.095219	0.184868**	0.205620***	1.000000				
Spain	0.019201	0.026021	0.006315	0.273864***	0.225676***	1.000000			
UK	0.074808	0.032210	0.182373**	0.170755**	0.026110	-0.004370	1.000000		
Others	0.098897	0.008834	0.144067**	0.291548***	0.189767***	0.032782	0.227489***	1.000000	
Total	0.285171***	0.132463	0.190179***	0.503991***	0.462236***	0.706878***	0.189970***	0.504700***	1.000000

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

As in Coimbra, for the series of returns from overnight stays in Lisbon, was held the unit root test (Appendix C) with all the time series simultaneously and was rejected the hypothesis of non-stationarity at the usual levels of significance (Table 18).

Table 18 - Summary for group unit root test for returns from Lisbon

Method	Statistic	Probability
Levin, Lin & Chu t	-36.8754	0.0000
Im, Pesaran and Shin W-stat	-43.6889	0.0000
ADF - Fisher Chi-square	903.333	0.0000
PP - Fisher Chi-square	654.519	0.0000

Source: author

Thereafter, the ADF tests for each of the individual series, were also performed, which confirmed the fact that it is not necessary to use cointegration, at the usual levels of significance (Table 19).

Table 19 - Summary of individual ADF tests for returns from Lisbon

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
ADF	-13.63***	-14.25***	-14.90***	-10.06***	-16.50***	-15.72***	-10.88***	-15.16***	-16.05***

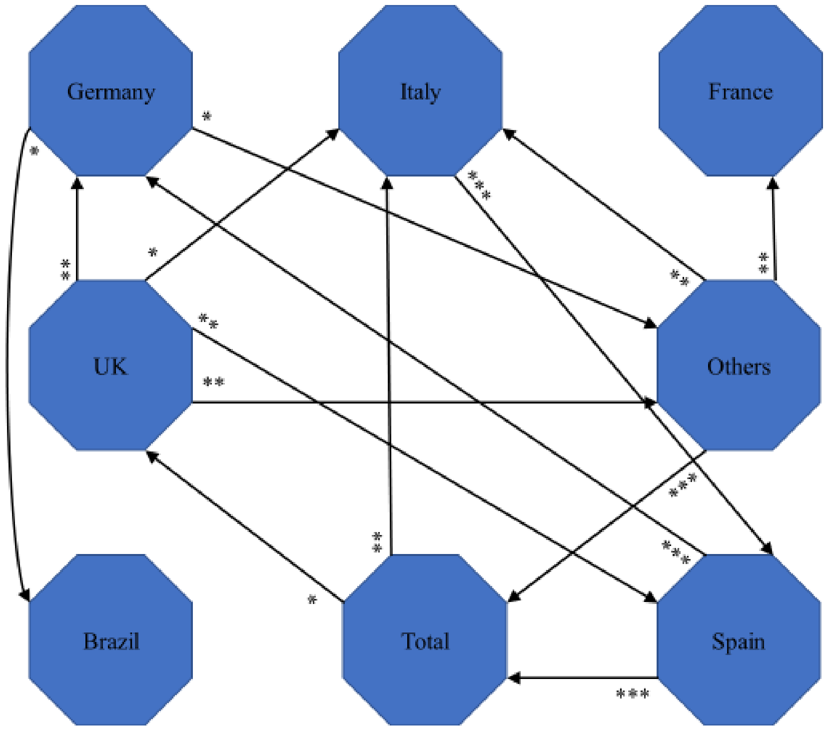
Note: *** denotes significance at 1% level; Others are non-specified countries.

Source: author

For the time series of returns of overnight stays, in Lisbon, variations in the series with data coming from Italy seem to cause changes in the time series with returns from Spain (like in Coimbra), variations in the latest seem to affect the series from Germany and with returns from total overnight stays, variations in the series from the United Kingdom seem to affect the series with the returns of overnight stays from Germany, Spain and non-specified countries. Variations in this last series seem to cause changes on those from France, Italy e from returns of total overnight stays, and, finally, variations in the returns from total overnight stays seem to affect series of returns from Italy, according to the Granger causality tests (Appendix D). There are no bidirectional causalities.

Except for changes in returns from the United Kingdom causing changes in returns from France, all the other unidirectional causalities coincide with previously identified statistically significant positive correlations. This analysis was performed taking into account a level of significance of 5%. Considering the different usual levels of significance (including the less rigorous level of 10%) we can observe all Granger causalities in Figure 39.

Figure 39 - Granger causalities for all source markets in Lisbon



Note: *** denotes significance at 1% level, **denotes significance at 5% level and * denotes significance at 10% level
Source: author

For each source market, models were estimated using OLS and ARDL specification and, the possibility of existence of autocorrelation, was statistically verified using BG tests. The results can be seen in Table 20 and it can be rejected that there is no autocorrelation of any order for all source markets for models without lags, but the problem of autocorrelation seems to be solved when lags are used in returns of overnight stays in Lisbon.

Table 20 - Statistics for BG tests for OLS and ARDL (with number of lags) models for returns in Lisbon

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
OLS	31.22***	31.66***	41.81***	33.27***	50.59***	95.27***	13.57***	34.28***	53.82***
ARDL	0.22	1.49	5.53	0.40	0.76	1.30	0.25	0.95	2.54
Number of lags	4	2	2	5	2	5	3	4	3

Note: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

For returns from overnight stays in Lisbon, the results of the heteroscedasticity LM tests are summarized in Table 21. It can be concluded that one can reject the null hypothesis of non-existence of ARCH up to order *l* in the models without lags.

Table 21 - LM tests statistics for OLS and ARDL models for returns in Lisbon

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
OLS	7.28***	17.97***	20.16***	8.94***	18.16***	34.78***	6.93***	48.73***	22.79***
ARDL	4.62**	18.47***	1.76	2.00	0.01	6.01**	1.05	0.77	0.53

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.
Source: author

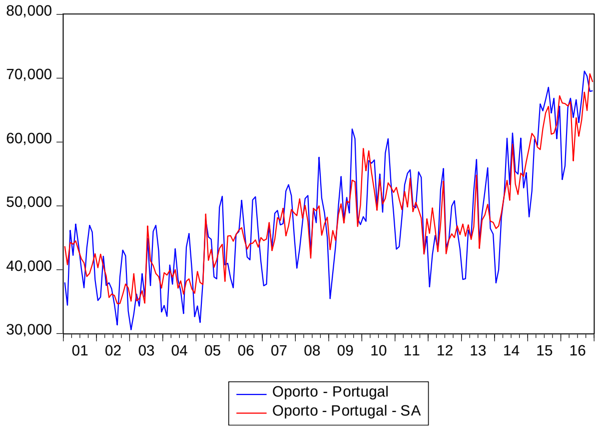
Heteroscedasticity problem is solved with ARDL specification in all source markets except for the returns from overnight stays in Lisbon, from Portugal, Brazil, Spain, where this problem persists, like in Coimbra.

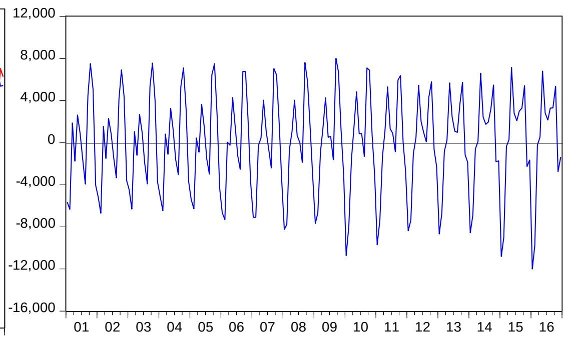
4.1.3. Overnight Stays in Oporto

Data on overnight stays from domestic tourism in Oporto, before and after seasonal adjustment (a) in combination with seasonality component (b) can be observed in Figure 40, which shows the non-existence of occasional events to be revised.

Figure 40 - Overnight stays (a) and seasonality component (b) in Oporto from Portugal

(a) (b)



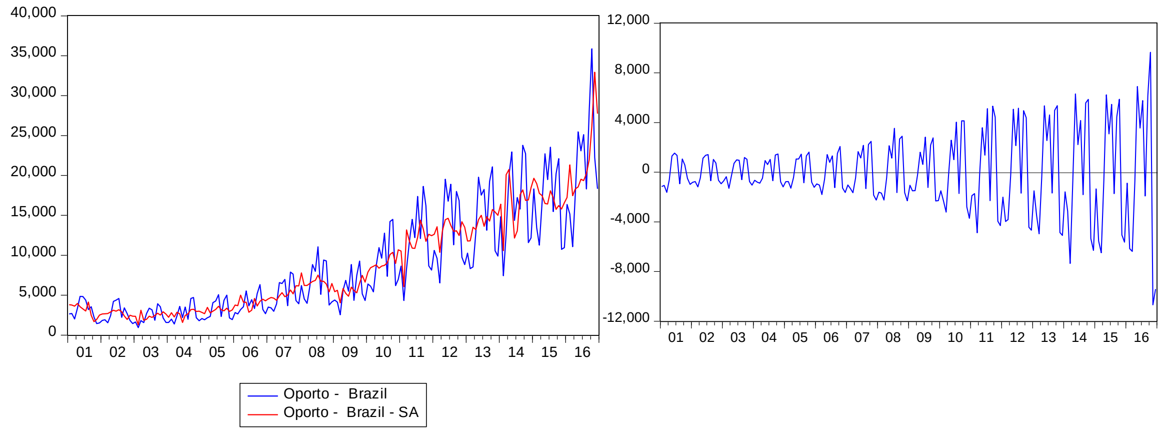


Source: author

Similarly, the time series with overnight stays, in Oporto, from Brazil (Figure 41) and from France (Figure 42), before and after the seasonal adjustment (a), in combination with the seasonality component (b), show the non-existence of occasionally events to be revised.

Figure 41 - Overnight stays (a) and seasonality component (b) in Oporto from Brazil

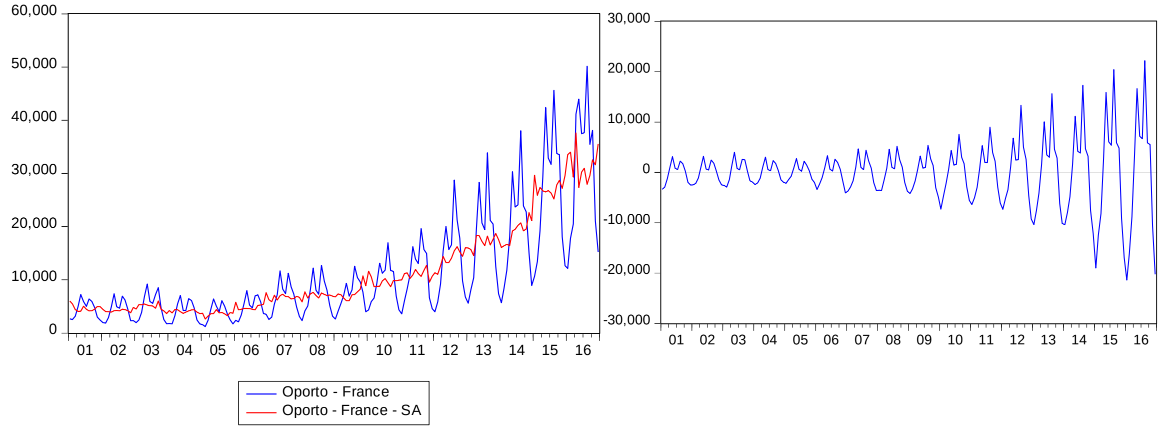
(a) (b)



Source: author

Figure 42 – Overnight stays (a) and seasonality component (b) in Oporto from France

(a) (b)

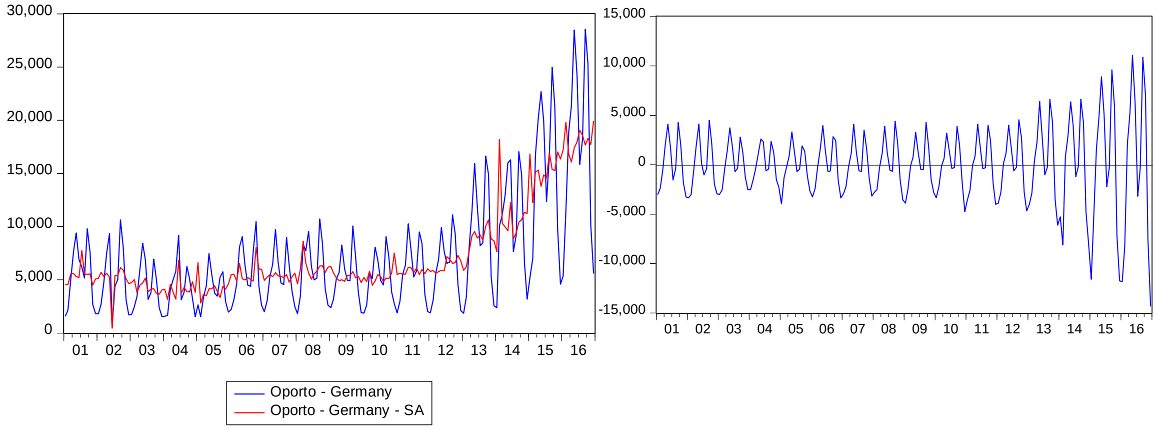


Source: author

Data on overnight stays, in Oporto, from Germany, before and after seasonal adjustment (a), in combination with seasonality component (b), can be observed in Figure 43, which allowed the identification of two occasional events: June 2002 and February 2014. In June 2002, the year when the Euro becomes the currency in most European countries, and in which the ‘Warm by Nature’ advertising campaign makes Portugal known inside the main emitting markets, there has been an explosion of two car bombs, in Spain. This terrorist attack, claimed by ETA, may had been reflected in tourism demand in Portugal, which, the following year, has been advertised as a safe country. In February 2014, Oporto was considered the Best European Destination ahead of other nineteen European cities. The results after correction of this value, before and after seasonality adjustment (a) and the final seasonality component (b) can be observed in Figure 44.

Figure 43 - Overnight stays (a) and seasonality component (b) in Oporto from Germany before event correction

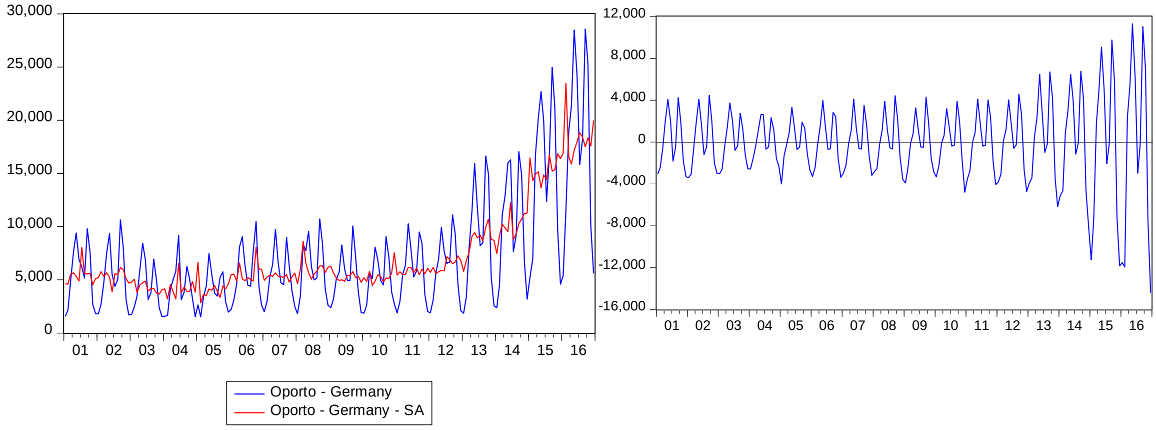
(a) (b)



Source: author

Figure 44 - Overnight stays (a) and seasonality component (b) in Oporto from Germany after event correction

(a) (b)

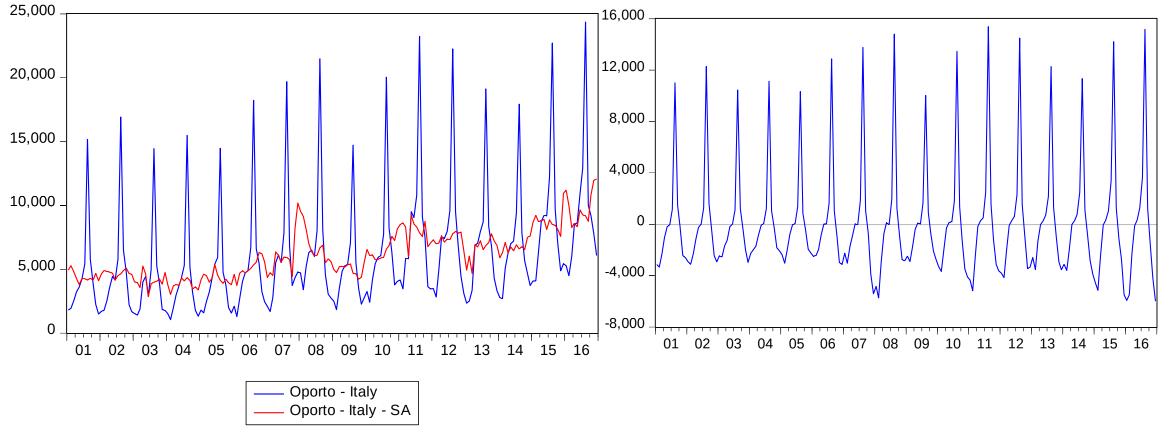


Source: author

With regard to overnight stays from Italy (Figure 45) and Spain (Figure 46) in Oporto, before and after seasonal adjustment (a), in combination with seasonality component (b), it can be observed the non-existence of irregular points in the time series.

Figure 45 - Overnight stays (a) and seasonality component (b) in Oporto from Italy

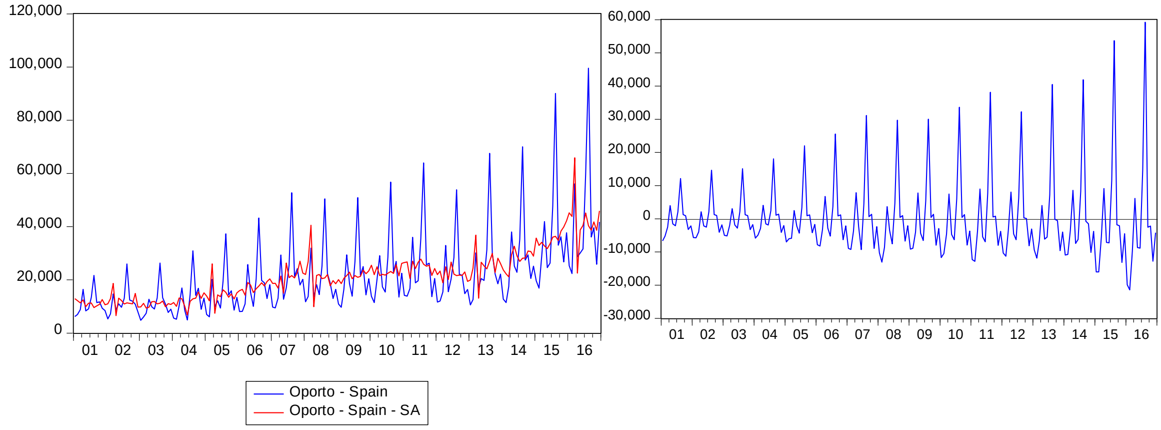
(a) (b)



Source: author

Figure 46 - Overnight stays (a) and seasonality component (b) in Oporto from Spain

(a) (b)

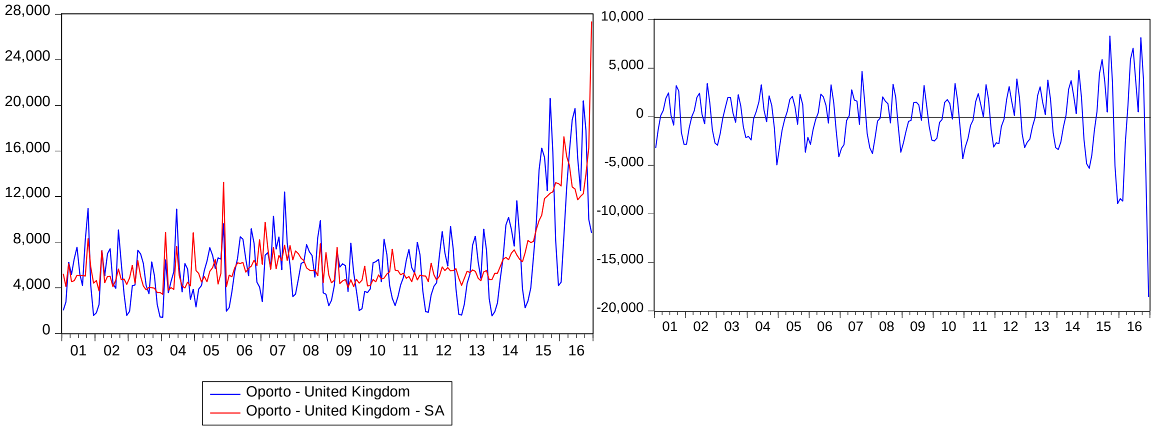


Source: author

From the United Kingdom to Oporto, overnight stays, before and after seasonal adjustment (a), conjugated with seasonality component (b), can be saw in Figure 47, which allowed the identification of two occasional events: November 2005 and December 2016. In November 2005, the 12th edition of the MTV Music Awards took place in Portugal, although in Lisbon there may have been influence on the results in the city of Oporto. On November 23, 2005 an UEFA Champions League match, between a Scottish team (The Rangers Football Club and Porto Football Club), took place in Oporto. In that season the English club Arsenal Football Club was a favourite one. In December 2016 a bilingual campaign (Portuguese / English) was held in Oporto where the city was promoted as ‘Porto. City with happy holidays’. São Silvestre Racing is organized in Porto every year and has thousands of participants. Also, the New Year's Eve with the traditional firework is very popular in this city. All of these facts may have influenced tourism demand in this city. Figure 48 shows the results after the correction of this value, before and after seasonal adjustment (a) and the respective seasonality component (b).

Figure 47 - Overnight stays (a) and seasonality component (b) in Oporto from United Kingdom before event correction

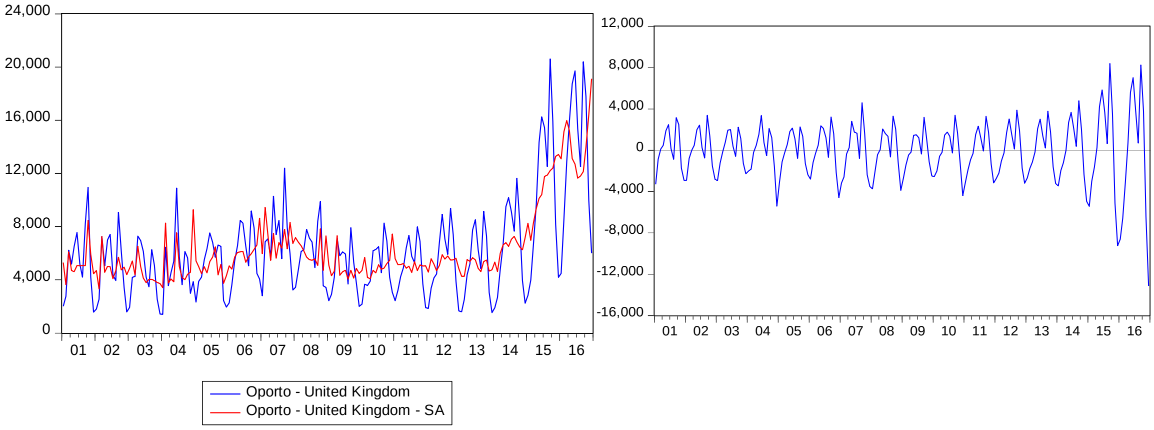
(a) (b)



Source: author

Figure 48 - Overnight stays (a) and seasonality component (b) in Oporto from United Kingdom after event correction

(a) (b)

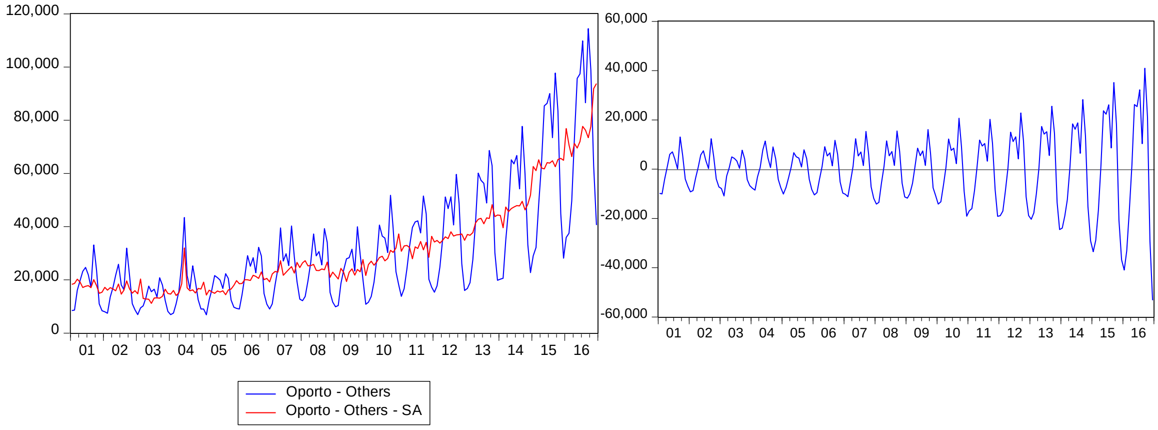


Source: author

With regard to overnight stays from other non-specified countries, in Oporto, the original data and data seasonally adjusted (a), as well as the seasonal component (b), can be seen in Figure 49, where we can verify the non-existence of sporadic events in the time series.

Figure 49 - Overnight stays (a) and seasonality component (b) in Oporto from non-specified countries

(a) (b)

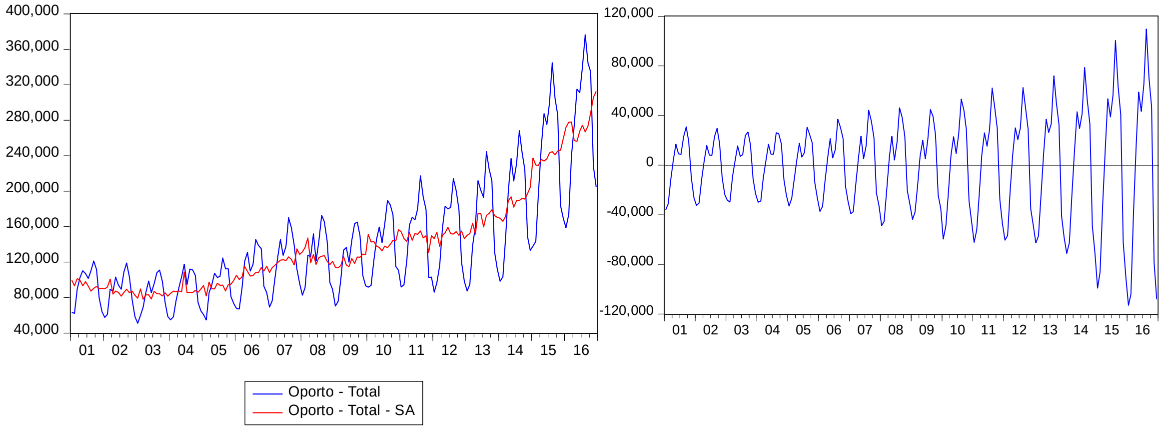


Source: author

Lastly, with regard to the total overnights, in Oporto, the original data and data with seasonal adjustment (a), as well as the seasonality component (b), can be observed in Figure 50, where, once again, we can verify the non-existence of irregular events in the time series.

Figure 50 - Total overnight stays (a) and seasonality component (b) in Oporto

(a) (b)

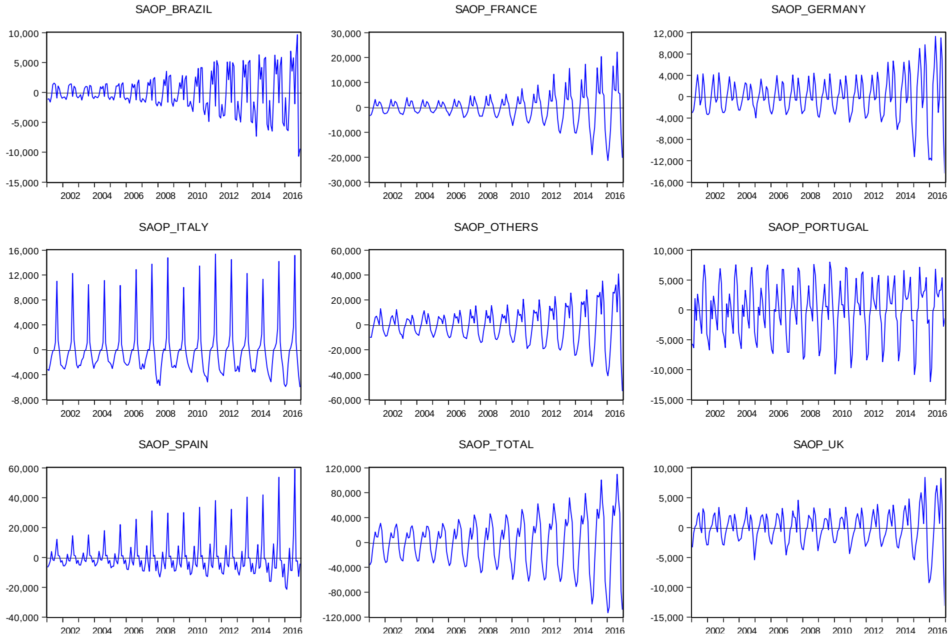


Source: author

All the time series of overnight stays in Oporto indicate a growing tendency with greater slope from the year 2014 forward.

Figure 51 illustrates seasonality components for seasonal adjusted time series with the overnights stays from all origins analysed in this study to Oporto. It can be observed the existence of situations of increasing variance for the time series relative to Brazil, France, Germany, Spain, the United Kingdom, other unspecified countries and total overnight stays. In the case of overnight stays from domestic tourism and also from Italy, the variance shows an approximately constant behaviour.

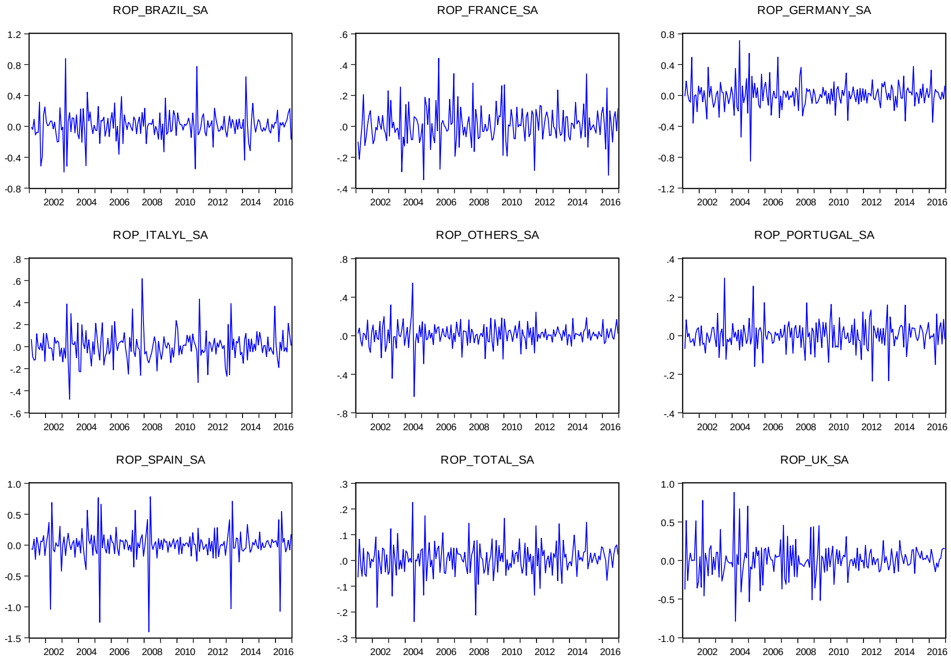
Figure 51 - Seasonality components after seasonal adjustment for overnight stays in Oporto



Source: author

The conversion of the seasonally adjusted series with the overnight stays in Oporto for series of returns, allowed the identification, for all source markets, of a variation of periods of greater (more intense zones of the chart) and less volatility (Figure 52) with more significance in France, the United Kingdom and total overnight stays.

Figure 52 - Time series of returns of overnight stays in Oporto



Source: author

The descriptive statistics of the returns of overnight stays in Oporto can be observed in Table 22. The returns with the highest mean are those from overnight stays from Brazil, as in the other cities studied, the lowest positive mean occurs with Portugal and, as in Lisbon, there are no source markets with negative returns mean. Except for Italy, 50% of the returns are positive.

Like in the other two cities, the coefficient of variation is quite high in all source markets, which indicates a large relative dispersion of data and little representativeness of the mean. The returns from overnight stays from Germany (as in Coimbra and Lisbon), Spain (also in the other two cities), non-specified countries (as in Lisbon) and total overnight stays (like in Coimbra and Lisbon) have negative asymmetry. As in the other two cities, all distributions are leptokurtic.

The Jarque-Bera statistic allows us to reject the hypothesis of the returns time series having a normal distribution for all source markets at the usual levels of significance (as in Coimbra) (Appendix A).

Table 22 - Descriptive statistics of the returns of overnight stays in Oporto from markets analysed

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
Mean	0.002426	0.010403	0.009281	0.007650	0.004683	0.006638	0.006713	0.008558	0.005988
Median	0.001073	0.012840	0.003417	0.006550	-0.003450	0.014854	0.006258	0.010920	0.005995
Maximum	0.298674	0.878354	0.441289	0.714008	0.618220	0.783432	0.883755	0.545887	0.225479
Minimum	-0.236569	-0.593693	-0.347281	-0.852682	-0.478468	-1.408128	-0.787019	-0.631790	-0.237738
Std. Dev.	0.072311	0.189942	0.118294	0.175940	0.135994	0.272116	0.220666	0.118516	0.062429
Coef. of Var.	29.81	18.26	12.75	23.00	29.04	40.99	32.87	13.85	10.43
Skewness	0.251178	0.388153	0.267828	-0.098767	0.629354	-1.550823	0.437020	-0.655386	-0.239426
Kurtosis	5.371303	7.357663	4.382075	7.363949	6.086588	11.72852	5.920924	9.486139	5.350286
Jarque-Bera	46.76***	155.92***	17.48***	151.87***	88.43***	682.88***	73.98***	348.48***	45.79***
Sum	0.463289	1.987046	1.772641	1.461097	0.894543	1.267949	1.282153	1.634603	1.143728
Sum Sq. Dev.	0.993485	6.854820	2.658755	5.881438	3.513913	14.06900	9.251744	2.668736	0.740505

Note: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

The correlations (Appendix B) between time series of returns from overnight stays, in Oporto, are show in Table 23. Returns of total overnight stays, in Oporto, are statistically positively correlated (low) with the returns from overnight stays from Portugal, France and Italy, and moderately with those from Germany, Spain, the United Kingdom and non-specified countries, according to Taylor's classification (1990). The only correlation that is not statistically significant is with the series of returns from overnight from Brazil.

Returns from overnight stays from non-specified countries, in Oporto, are statistically negatively correlated (low) with returns from Brazil, positively correlated (low) with those from France and Italy, and positively (moderated) with returns from the United Kingdom and Germany. This last one is statistically negatively correlated (low) with return from Brazil.

From Italy, returns of overnight stays in Oporto are statistically positively correlated (low) to returns from Germany and France. The latter are also statistically positively correlated (low) with the Portugal.

In comparison with the results of the correlations between the analysed time series of the same markets in Coimbra and Lisbon, regardless of the correlation intensity, some differences were identified. With regard to the returns from overnight stays from France, in Coimbra, only are statistically correlated with those from Spain, which is not the case in Lisbon or Oporto. In this latter city, they are correlated with the Italian market, with non-specified countries and with total overnight stays (which is not the case in Coimbra) and in Lisbon, they are statistically correlated with the German market and those from the United Kingdom, which does not happen in Oporto.

The returns from the Brazilian market are only statistically correlated with the domestic market and with total overnight stays in the city of Coimbra. Both in Lisbon and in Oporto this market is correlated with the German market and is also correlated with unspecified cities in the city of Oporto (which is not the case in Coimbra). Only in the city of Oporto the returns from overnight stays from France are statistically correlated with the domestic market. Italian market is only correlated with domestic and Spanish markets in Lisbon.

Returns from overnight stays from the German market are statistically correlated with those coming from Spain and the United Kingdom, in the cities of Coimbra and Lisbon, a fact that does not occur in Oporto.

Table 23 - Correlations between returns of overnight stays in Oporto from different markets

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Portugal	1.000000								
Brazil	0.005793	1.000000							
France	0.142066**	-0.056057	1.000000						
Germany	-0.036184	-0.171669**	0.139606	1.000000					
Italy	0.098993	-0.068645	0.211296***	0.219623***	1.000000				
Spain	-0.066756	0.064988	-0.076621	0.052975	-0.039893	1.000000			
UK	0.052367	0.022477	-0.010123	0.082943	0.015499	-0.014051	1.000000		
Others	0.090302	-0.178926**	0.188480***	0.413002***	0.186046***	-0.130969	0.443311***	1.000000	
Total	0.347866***	-0.021570	0.210510***	0.413557***	0.248817***	0.453939***	0.440331***	0.611703***	1.000000

Note: *** denotes significance at 1% level and ** denotes significance at 5% level; Others are non-specified countries.

Source: author

Also, with all the series of returns from overnight stays in Oporto, simultaneously, such as in Coimbra and Lisbon, the unit root test (Appendix C) allowed to reject the hypothesis of non-stationarity at the usual levels of significance (Table 24).

Table 24 - Summary for group unit root test for returns from Oporto

Method	Statistic	Probability
Levin, Lin & Chu t	-51.1087	0.0000
Im, Pesaran and Shin W-stat	-50.5198	0.0000
ADF - Fisher Chi-square	925.627	0.0000
PP - Fisher Chi-square	356.152	0.0000

Source: author

As in the other cities, the ADF tests were carried out for each of the time series, individually, which confirmed the fact of not being necessary to use cointegration, also at the usual levels of significance (Table 25).

Table 25 - Summary of individual ADF tests for returns from Oporto

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
ADF	-15.18***	-15.23***	-20.02***	-15.24***	-17.25***	-12.07***	-11.94***	-14.75***	-22.81***

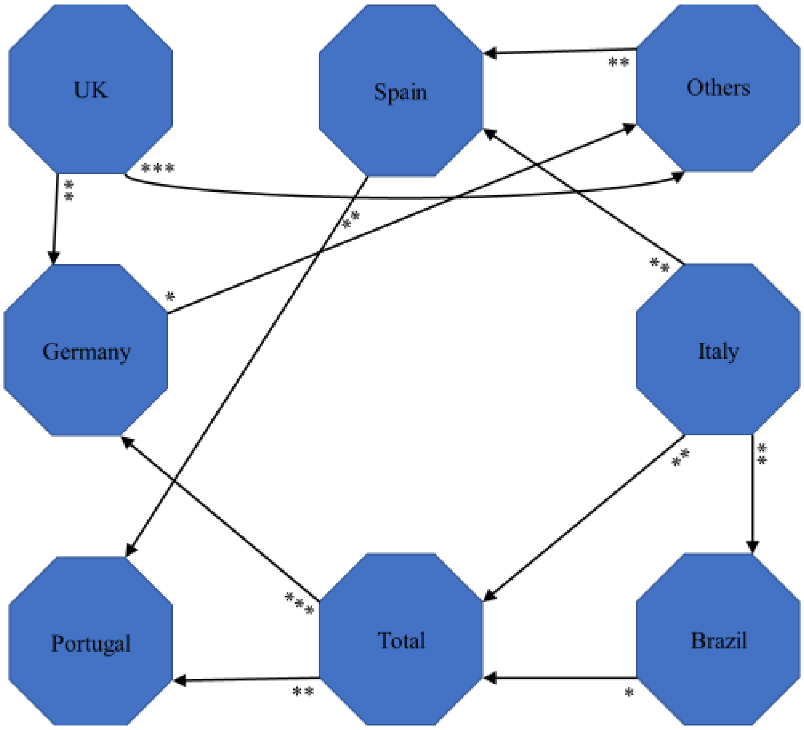
Note: *** denotes significance at 1% level; Others are non-specified countries.

Source: author

The Granger causality tests (Appendix D) had shown that, for the series of returns of overnight stays in Oporto, variations in the series from Italy seem to affect the series with the returns of overnight stays from Brazil, Spain (as in Coimbra and Lisbon) and with returns from total overnight stays, variations in the series with data coming from Spain seem to cause changes in the time series with returns from Portugal, variations in the series from United Kingdom seem to affect the series with the returns of overnight stays from Germany and non-specified countries (both like in Lisbon), variations in this last series seem to cause changes on those from Spain, and, finally, variations in the returns from total overnight stays seem to affect series of returns from Portugal and Germany. There are no bidirectional causalities. These are the conclusions according to a significance level of 5%.

Only four of these nine unidirectional causalities coincide with statistically significant conclusions from the analysis of correlations. In Figure 53 all Granger causalities can be observed considering all usual levels of significance.

Figure 53 - Granger causalities for all source markets in Oporto



Note: *** denotes significance at 1% level, **denotes significance at 5% level and * denotes significance at 10% level

Source: author

Also, for the returns from overnight stays, in Oporto, for each source market, models were estimated using OLS and ARDL specification and the possibility of the existence of autocorrelation, was statistically verified using BG tests. The results can be seen in Table 26 and it can be rejected that there is no autocorrelation of any order for all source markets for models without lags, but the problem of autocorrelation seems to be solved when lags are used in returns from overnight stays in Oporto, like in Lisbon.

Table 26 - Statistics for BG tests for OLS and ARDL (with number of lags) models for returns in Oporto

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
OLS	49.90***	44.43***	27.40***	56.09***	13.97***	89.82***	54.83***	42.14***	46.69***
ARDL	0.76	0.02	0.34	2.46	0.86	4.56	0.04	2.65	1.07
Number of lags	4	4	5	7	6	5	2	4	5

Note: *** denotes significance at 1% level; Others are non-specified countries.

Source: author

In Table 27 results of the heteroscedasticity LM tests are summarized for returns from overnight stays, in Oporto, and it can be concluded that the null hypothesis of non-existence of ARCH up to order l in the models without lags can be rejected. ARDL specification does solve heteroscedasticity problem in all source markets except for the returns from overnight stays in Oporto, from Brazil, Italy, Spain and non-specified countries, where this problem persists.

Table 27 - LM tests statistics for OLS and ARDL models for returns in Oporto

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
OLS	9.30***	39.89***	8.97***	26.69***	9.32***	27.04***	33.33***	35.94***	14.44***
ARDL	0.06	21.12***	0.16	1.11	7.52***	26.28***	0.01	10.68***	3.12

Note: *** denotes significance at 1% level; Others are non-specified countries.
Source: author

The problem of heteroscedasticity with models with ARDL for returns from Brazil and Spain is common to the tree cities analysed in this thesis, and with model with ARDL for returns from non-specified countries, occurred also with Coimbra data.

4.2. ARCH/GARCH models

In this section, the returns of overnight stays were used to estimate ARCH(1) or GARCH(1,1) for all cities and for all source markets analysed (Appendix F and Appendix G). The number of lags of the models with ARDL was calculated taking into account the lags of Table 14, Table 20 and Table 26 and adjusted according to the coefficients significance of the lags of the returns added to the model, as well as the significance of the GARCH component, that is, β. The models are summarized in Table 28.

The results for the returns of overnight stays from Portugal, Brazil, Spain, the United Kingdom and the total number of overnight stays, in Coimbra, show, statistically significant coefficients for both ARDL and non-ARDL models. The same happens with the models for the returns of overnight stays coming from Brazil, France, non-specified countries and total overnight stays, in Lisbon, and for the returns of overnight stays, in Oporto, from Brazil, Germany, Italy, Spain and non-specified countries.

In Coimbra, for the returns from France, Germany, Italy and non-specified countries the models ARCH/GARCH with ARDL have statistically non-significant coefficients, whereas the models without ARDL does not present this problem.

The previous situation also occurs in the models for the returns from Portugal, Germany, Italy, the United Kingdom and total overnight stays, in Lisbon, and from France, the United Kingdom and total overnight stays, in Oporto.

In addition to the problem, related to the non-negativity constraints, it exists in Lisbon for the returns from Spain, in the model without ARDL, being corrected in the model with lags, and also in Oporto, for the returns from Portugal, where the problem remains before and after ARDL.

According to the Wald test on $\alpha = 1$ in the ARCH models and $\alpha + \beta = 1$ in the GARCH models, in Coimbra, the ARCH/GARCH models for returns of overnight stays from Portugal, Brazil and Spain, without ARDL, and from Brazil and Italy, with ARDL, do not appear to have finite memory, which means that there is no recovery time. The same happens with models obtained for Lisbon, from Spain, without ARDL, and from Italy and the United Kingdom, with ARDL. With respect to Oporto, this problem of persistence, occurs for returns from Spain and non-specified countries, without ARDL, and from France, Spain and the United Kingdom, with ARDL.

Results from heteroscedasticity LM tests are presented in Table 29, where it can be concluded that, in all the ARCH/GARCH models with returns from overnight stays, in Coimbra, there is no conditional heteroscedasticity in the residuals. In Lisbon, for the GARCH model for the returns from overnight stays from Spain, with no ARDL, and, in Oporto, for the GARCH model for the returns of overnight stays from Brazil, with no ARDL, the null hypothesis of this test, should be rejected. So, in these two models, it exists conditional heteroscedasticity in the residuals.

Table 28 - Summary of the ARCH/GARCH models applied to returns for all source markets and all cities

		Portugal		**Brazil**		**France**		**Germany**		**Italy**		**Spain**		**UK**		**Others**		**Total**	
Coimbra	ω	0.0029***	0.0046***	0.0120***	0.0027*	0.0284***	0.0350***	0.0369***	0.0391***	0.0443***	0.0057	0.0325***	0.0306***	0.0440***	0.0333***	0.0182***	0.0184***	0.0045***	0.0036***
	α	0.5909***	0.3792***	0.3955***	0.1638***	0.4751***	-0.0763	0.3094***	-0.0045	0.2459**	0.0230	0.8898***	0.4836***	0.3453***	0.3126***	0.3221**	0.1297	0.3774***	0.4235***
	β	0.1796**		0.4173***	0.7790***						0.8281***								
	Number of lags	0	4	0	2	0	3	0	3	0	6	0	7	0	6	0	5	0	2
Lisbon	ω	0.0016***	0.0016***	0.0107***	0.0101***	0.00523***	0.0056***	0.0022**	0.0061***	0.0093***	0.0015	0.0181***	0.0151***	0.0064***	0.0009	0.0021***	0.0019***	0.0022***	0.0020***
	α	0.3164***	0.1670	0.4587***	0.4213***	0.3695***	0.0658***	0.2462**	0.2063	0.3683***	0.0128	0.9203***	0.6011***	0.1816*	0.0572	0.4724***	0.5331***	0.2554***	0.0967
	β							0.5264***			0.8303***	-0.0462**			0.8069***				
	Number of lags	0	2	0	2	0	2	0	4	0	2	0	3	0	3	0	1	0	2
Oporto	ω	0.0047***	0.0003***	0.0103***	0.0207***	0.0110***	0.0031	0.0154***	0.0147***	0.0098***	0.0102***	0.0126***	0.0089***	0.0267***	0.0002	0.0047***	0.0054***	0.0027***	0.0026***
	α	0.3383***	-0.0568***	0.4168***	0.2167**	0.2050*	-0.0358	0.5097***	0.2530***	0.5691***	0.4512***	1.1850***	1.0844***	0.4442***	0.0523**	0.7877***	0.5287***	0.2991***	0.1200
	β	-0.2350**	0.9767***	0.3162***			0.7734***								0.9373***				
	Number of lags	0	2	0	3	0	0	2	7	0	4	0	4	0	3	0	2	0	2

Notes: ***denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; Others are non-specified countries; Lags are used in the mean equation.

Source: author

Table 29 - LM tests for the ARCH/GARCH models applied to returns for all source markets and all cities

	Portugal		Brazil		France		Germany		Italy		Spain		UK		Others		Total	
	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL
Coimbra	0.0001	0.2833	0.6624	0.7795	1.3237	0.0061	0.3041	0.0002	0.7586	0.1428	1.8896	0.5418	0.8690	0.0183	0.0015	0.0301	0.0129	1.3934
Lisbon	0.0184	0.0045	1.5298	0.5313	0.2923	0.0896	2.0975	0.0057	0.0529	0.0362	5.0196**	0.42314	0.3135	0.0498	0.0942	0.5229	0.9509	0.0094
Oporto	0.0203	0.8885	3.4132*	1.2529	0.0575	0.1258	0.2082	0.0480	0.0037	0.1030	3.2917	1.6928	0.4039	0.3708	2.6971	1.5161	0.5474	0.0079

Note: ** denotes significance at 5% level and * denotes significance at 10% level; Others are non-specified countries.
Source: author

4.3. EGARCH models

The returns from overnight stays in the three cities under analysis, from all source markets, were used to estimate the EGARCH models, with and without ARDL (Appendix H and Appendix I). The number of lags of the ARDL models was chosen based on the statistical significance of the coefficients, starting from the inclusion of the lags from Table 14, Table 20 and Table 26. Also, the inclusion of the GARCH component in these models, was analysed using the statistical significance of its coefficient. The results are summarized in Table 30.

For returns from overnight stays in Coimbra, the EGARCH models with all coefficients statistically significant are those from Portugal, Brazil, Spain, the United Kingdom and from total overnight stays, with ARDL. The coefficients are all statistically significant in the non-ARDL EGARCH models with returns of overnight stays from Brazil, Germany and non-specified countries, and in the EGARCH models with ARDL, for returns from France, Spain, non-specified countries and total overnight stays in Lisbon. In Oporto, only overnight stays from Italy, originated returns whose model EGARCH without ARDL has all coefficients statistically significant. With respect to the EGARCH models with ARDL, the models that were obtained with all the coefficients statistically significant, were for returns from Portugal, Spain and non-specified countries.

From the models mentioned in the previous paragraph, we can also see that, in Coimbra, volatility increases with the increase in tourism demand (measured in overnight stays) by Portugal, Spain (as well as in Lisbon and Oporto) and in relation to total overnight stays (as in Lisbon). The same happens in Lisbon, for overnight stays from Germany and non-specified countries (as well as in Oporto). Volatility increases with the decrease in tourism demand for overnight stays from Portugal and Italy (in Oporto), Brazil (in Lisbon and in Coimbra), France (in Lisbon) and the United Kingdom (in Coimbra).

Outcomes from heteroscedasticity LM tests are presented in Table 31. It can be concluded that in all EGARCH models with returns from overnight stays in Coimbra, Lisbon and Oporto there is no conditional heteroscedasticity in the residuals.

Table 30 - Summary of the EGARCH models applied to returns for all source markets and all cities

		Portugal		Brazil		France		Germany		Italy		Spain		UK		Others		Total	
Coimbra	ω	-4.2246***	-3.3224***	-1.4082***	-3.3784***	-3.7216***	-3.4964***	-2.4436***	-3.2138***	-5.0358***	-3.2403***	-2.6027***	-3.4790***	-2.0588***	-3.5470***	-4.1060***	-4.1442***	-1.9110**	-5.646***
	α	0.9820***	0.5953***	0.6738***	0.3398*	0.7722***	0.1014	0.8654***	-0.0470	0.5255***	0.0284	0.9848***	0.4083*	0.7301***	0.5462***	0.5055***	0.3855**	0.5396***	0.4563***
	γ	0.1510	0.1871*	-0.0461	-0.306117***	-0.0070	-0.2859***	0.2026	0.0303	0.0035	0.1217	0.2095	0.4034***	-0.1031	-0.2035*	0.0445	-0.0224	0.1383	0.2946***
	β	0.2940**	0.4415***	0.7090***				0.4202***		-0.5920***		0.3178***		0.4778***				0.7050***	
	Number of lags	0	4	0	3	0	3	0	3	0	4	0	7	0	6	0	5	0	2
Lisbon	ω	-6.6190***	-6.5044***	-6.1606***	-6.5004***	-2.9163***	-9.6045***	-1.7734***	-2.1158*	-4.8058***	-0.7559	-3.3816***	-5.7456***	-5.1395***	-0.7384	-3.2775***	-3.2011***	-6.2690***	-6.2685***
	α	0.5513***	0.2716*	0.6785***	0.6024***	0.4830***	0.1698*	0.4661***	0.3793*	0.5853***	0.0583	1.2432***	0.5424***	0.3352**	0.1587*	0.5140***	0.3718**	0.4901***	0.1701***
	γ	-0.0825	-0.1558	-0.1548*	-0.1172	-0.0648	-0.1263*	0.2556**	0.0172	0.0509	-0.0307	0.0002	0.3536***	0.1229	-0.0093	0.3994***	0.4092***	0.0884	0.1782***
	β			-0.3286**	-0.3896***	0.4775***	-0.8472***	0.7026***	0.6311***		0.8457***	0.2899***	-0.3632***		0.8762***	0.4984***	0.5030***		
	Number of lags	0	2	0	2	0	2	0	4	0	2	0	3	0	3	0	2	0	2
Oporto	ω	-5.7963***	-0.5222***	-1.9246***	-1.7305***	-4.5686***	-4.2952***	-4.3098***	-4.5631***	-4.7947***	-5.6231***	-2.9052***	-4.7795***	-3.7792***	-6.8503***	-5.5537***	-5.4850***	-6.1070***	-5.9968***
	α	0.5857***	-0.3997***	0.6642***	0.1750	0.3445**	-0.1388	0.7720***	0.7464***	0.6816***	0.6953***	1.2500***	1.1305***	0.7477***	-0.0117	1.0446***	0.8606***	0.5857***	0.1919
	γ	-0.0115	-0.0678***	-0.1116	-0.3565***	-0.0223	-0.0806	0.0762	-0.0466	-0.4650***	-0.3799***	0.1513	0.2241**	-0.0061	-0.2535***	0.1480	0.1844*	0.1242	0.1263
	β		0.8535***	0.6045***	0.5629***						-0.1831	0.4158***			-0.9023***				
	Number of lags	0	4	0	2	0	1	0	7	0	3	0	4	0	5	0	2	0	2

Notes: ***denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; Others are non-specified countries; Lags are used in the mean equation.
Source: author

Table 31 - LM tests for the EGARCH models applied to returns for all source markets and all cities

	Portugal		**Brazil**		**France**		**Germany**		**Italy**		**Spain**		**UK**		**Others**		**Total**	
	No ARDL	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**
Coimbra	0.4303	0.0014	0.2830	0.0230	0.3919	0.4324	0.0350	0.0723	0.6653	0.0760	0.1715	0.0073	0.0567	0.1829	0.0024	0.0115	0.0378	0.2548
Lisbon	0.0067	0.1760	0.0393	0.0978	0.8904	1.7938	0.6318	0.0316	0.0327	0.0563	0.0520	0.0001	0.0586	0.0391	0.3954	0.0533	0.2108	0.1594
Oporto	0.0001	1.2731	0.1608	0.4079	0.1951	0.0087	0.1395	0.3061	0.0019	0.0006	0.1305	0.2369	0.0097	1.9742	0.7680	0.2669	0.0017	0.0038

Note: Others are non-specified countries.
Source: author

Long-run covariance matrixes are shown in Table 32, Table 33 and Table 34 for returns from overnight stays in Coimbra, Lisbon and Oporto, respectively. Results could be compared with variance series mean, summarized in Table 35, for the three cities in analysis.

Table 32 - Long-run covariance matrix for returns from overnight stays in Coimbra

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Portugal	0.0027	0.0017	0.0008	0.0009	0.0011	0.0004	0.0007	0.0007	0.0017
Brazil	0.0017	0.0193	0.0006	0.0040	0.0069	0.0020	0.0004	0.0024	0.0026
France	0.0008	0.0006	0.0115	0.0017	0.0029	-0.0021	0.0022	0.0019	0.0009
Germany	0.0009	0.0040	0.0017	0.0145	0.0040	0.0033	0.0038	0.0057	0.0024
Italy	0.0011	0.0069	0.0029	0.0040	0.0141	0.0043	0.0030	0.0034	0.0025
Spain	0.0004	0.0020	-0.0021	0.0033	0.0043	0.0211	0.0022	0.0023	0.0035
UK	0.0007	0.0004	0.0022	0.0038	0.0030	0.0022	0.0208	0.0058	0.0026
Others	0.0007	0.0024	0.0019	0.0057	0.0034	0.0023	0.0058	0.0087	0.0026
Total	0.0017	0.0026	0.0009	0.0024	0.0025	0.0035	0.0026	0.0026	0.0022

Note: Others are non-specified countries.
Source: author

Table 33 - Long-run covariance matrix for returns from overnight stays in Lisbon

	Portugal	**Brazil**	**France**	**Germany**	**Italy**	**Spain**	**UK**	**Others**	**Total**
Portugal	0.0008	0.0003	0.0002	0.0001	0.0006	0.0002	0.0004	0.0002	0.0004
Brazil	0.0003	0.0079	0.0001	0.0008	0.0008	-0.0001	0.0006	0.0007	0.0007
France	0.0002	0.0001	0.0035	0.0009	0.0010	0.0009	0.0013	0.0007	0.0007
Germany	0.0001	0.0008	0.0009	0.0031	0.0013	0.0016	0.0014	0.0009	0.0010
Italy	0.0006	0.0008	0.0010	0.0013	0.0044	0.0022	0.0004	0.0008	0.0012
Spain	0.0002	-0.0001	0.0009	0.0016	0.0022	0.0111	0.0007	0.0003	0.0020
UK	0.0004	0.0006	0.0013	0.0014	0.0004	0.0007	0.0039	0.0010	0.0010
Others	0.0002	0.0007	0.0007	0.0009	0.0008	0.0003	0.0010	0.0014	0.0008
Total	0.0004	0.0007	0.0007	0.0010	0.0012	0.0020	0.0010	0.0008	0.0010

Note: Others are non-specified countries.
Source: author

Table 34 - Long-run covariance matrix for returns from overnight stays in Oporto

	Portugal	Brazil	France	Germany	Italy	Spain	UK	Others	Total
Portugal	0.0014	0.0006	0.0006	0.0002	0.0008	0.0007	0.0004	0.0003	0.0008
Brazil	0.0006	0.0102	0.0009	0.0004	0.0015	0.0017	0.0001	0.0004	0.0009
France	0.0006	0.0009	0.0060	0.0011	0.0012	0.0007	0.0008	0.0006	0.0009
Germany	0.0002	0.0004	0.0011	0.0075	0.0020	0.0016	0.0024	0.0023	0.0014
Italy	0.0008	0.0015	0.0012	0.0020	0.0081	0.0019	0.0018	0.0022	0.0017
Spain	0.0007	0.0017	0.0007	0.0016	0.0019	0.0127	0.0008	-0.0004	0.0018
UK	0.0004	0.0001	0.0008	0.0024	0.0018	0.0008	0.0123	0.0031	0.0018
Others	0.0003	0.0004	0.0006	0.0023	0.0022	-0.0004	0.0031	0.0042	0.0015
Total	0.0008	0.0009	0.0009	0.0014	0.0017	0.0018	0.0018	0.0015	0.0013

Note: Others are non-specified countries.
Source: author

In Coimbra, for all series of returns, for all source markets, about 20% to 30% of the total variance is long-term variance, the highest value was obtained for data from Brazil (33% of the variance is long-term) and the lowest value obtained for returns from overnight stays from Spain (20% of the variance is long term). In Lisbon, long-term variance takes on more heterogeneous values than in Coimbra, ranging from only 16% of long-term variance, for data from Spain, and 50% of long-term variance, for data from the United Kingdom. The lowest return occurs for the data coming from Spain as in Coimbra but the remaining values are all higher than for Coimbra city. Finally, for Oporto, the percentages of long-term variance are generally higher than in Coimbra and lower than in Lisbon. Returns with the lowest percentage of long-term variance are those from Spain (17% of long-term variance), as in the other two cities, and the highest values occur for data from France and Italy (43% long-term variance).

Table 35 - Comparison of the long-run variances with the mean of the EGARCH series without ARDL

	Coimbra			Lisbon			Oporto		
	Long-Run Variance	Mean EGARCH No ARDL	% Related to EGARCH	Long-Run Variance	Mean EGARCH No ARDL	% Related to EGARCH	Long-Run Variance	Mean EGARCH no ARDL	% Related to EGARCH
Portugal	0,0027	0,0099	27%	0,0008	0,0022	35%	0,0014	0,0052	28%
Brazil	0,0193	0,0581	33%	0,0079	0,0180	44%	0,0102	0,0352	29%
France	0,0115	0,0514	22%	0,0035	0,0084	41%	0,0060	0,0139	43%
Germany	0,0145	0,0617	24%	0,0031	0,0099	31%	0,0075	0,0292	26%
Italy	0,0141	0,0602	23%	0,0044	0,0141	31%	0,0081	0,0188	43%
Spain	0,0211	0,1076	20%	0,0111	0,0677	16%	0,0127	0,0757	17%
UK	0,0208	0,0697	30%	0,0039	0,0079	50%	0,0123	0,0488	25%
Others	0,0087	0,0265	33%	0,0014	0,0039	36%	0,0042	0,0120	35%
Total	0,0022	0,0072	31%	0,0010	0,0031	32%	0,0013	0,0039	35%

Note: Others are non-specified countries.
Source: author

4.4. TGARCH models

In this subchapter, returns of overnight stays were used to estimate TGARCH models for all cities and for all source markets analysed, with and without ARDL (Appendix J and Appendix K). The number of lags considered in the models with ARDL was selected taking into account the lags of Table 14, Table 20 and Table 26 and the statistical significance of the coefficients, as well as the inclusion of the GARCH component, β, that was also analysed using its statistically significance. The outcomes are summarized in Table 36.

The TGARCH models with the returns of overnight stays from Spain in Coimbra, Lisbon and Oporto, and from non-specified countries in Lisbon and Oporto, show statistically significant coefficients for both ARDL and non-ARDL models.

For returns from overnight stays from Germany in Lisbon the TGARCH model with no ARDL has all coefficients statistically significant. The coefficients are all statistically significant in the TGARCH models with ARDL for returns of overnight stays from Portugal (in Coimbra and Oporto), Brazil (in Lisbon and Oporto), France, Germany and total overnight stays in Coimbra. For the returns from France and Germany in Coimbra, Brazil in Lisbon and Oporto and Portugal in Oporto there are problems related to the non-negativity constraints.

In the models mentioned in the previous paragraph, excluding those that do not check the TGARCH constraints we can also affirm that, in Coimbra, volatility increases with the increase in tourism demand (measured in overnight stays) by Portugal, Spain (as well as in Lisbon and

Oporto) and in relation to total overnight stays. The same happens in Lisbon, for overnight stays from non-specified countries (as well as in Oporto). Volatility increases with the decrease in tourism demand for overnight stays from Germany in Lisbon.

According to the Wald test on $\alpha + \frac{\gamma}{2} = 1$, in the TARCH models, and $\alpha + \beta + \frac{\gamma}{2} = 1$, in the TGARCH models, in Coimbra, models for returns of overnight stays from Brazil, Germany and Spain, without ARDL, and from Brazil and Spain, with ARDL, do not appear to have finite memory, which means that there is no recovery time. The same happens with models obtained for Lisbon, from Germany, Spain, and non-specified countries without ARDL, and from Italy and non-specified countries, with ARDL. With respect to Oporto, this problem of persistence occurs for returns from Italy, Spain and non-specified countries, without ARDL, and from Italy, Spain and the United Kingdom, with ARDL.

Conclusions about persistence in the TGARCH models were identical to those from ARCH/GARCH models except for returns from overnight stays from Portugal and Germany no ARDL and from Italy and Spain with ARDL in Coimbra, from Germany and non-specified countries, no ARDL and the United Kingdom and non-specified countries, with ARDL in Lisbon, and finally, from Italy no ARDL and from France and Italy with ARDL in Oporto.

Heteroscedasticity LM tests are summarized in Table 37, where it can be concluded that in the TGARCH models with returns from overnight stays in Coimbra we should reject the null hypothesis of no conditional heteroscedasticity in the residuals from Spain with ARDL, in Lisbon, for the TGARCH model for the returns of overnight stays from Spain, with and without ARDL, and in Oporto for the TGARCH model for the returns of overnight stays from Spain, with no ARDL, so in these four models it exists conditional heteroscedasticity in the residuals.

Table 36 - Summary of the TGARCH models applied to returns for all source markets and all cities

		Portugal		Brazil		France		Germany		Italy		Spain		UK		Others		Total	
Coimbra	ω	0.0046***	0.0054***	0.0119***	0.0078**	0.0284***	0.0301***	0.0213***	0.0735***	0.0439***	0.0400***	0.0319***	0.0190*	0.0439***	0.0335***	0.0182***	0.0184***	0.0047***	0.0035***
	α	0.7846**	0.5229**	0.3558**	0.0352	0.4705	-0.0916**	0.8368**	-0.0894***	0.3007*	0.0456	1.7967***	0.1503**	0.2245	0.1930	0.5211**	0.1469	0.4631***	0.7398***
	γ	-0.4449	-0.5989**	0.0862	0.4223**	0.0081	0.5413**	-0.6122	0.1090***	-0.0904	-0.1096	-1.6026***	-0.2384***	0.2651	0.2314	-0.3507	-0.0317	-0.2463	-0.6060**
	β			0.4179***	0.6310***			0.1965**	-0.8681***				0.5691**						
	Number of lags	0	4	0	2	0	4	0	4	0	4	0	7	0	6	0	5	0	2
Lisbon	ω	0.0015***	0.0016***	0.0108***	0.0049***	0.0052***	0.0055***	0.0022**	0.0061***	0.0093***	0.0017	0.0177***	0.0025***	0.0066***	0.0068***	0.0020***	0.0019***	0.0022***	0,0000**
	α	0.2399*	0.0633	0.1057	-0.0572***	0.3455***	0.0529	0.6042**	0.2059	0.3450	-0.0023	1.7994***	0.2233***	0.3008	0.1062	1.0683**	1.1096***	0.3949**	-0.0012
	γ	0.1806	0.2787	0.7626**	0.3947***	0.0666	0.0669	-0.5284*	0.0012	0.0440	0.0648	-1.5764***	-0.2962***	-0.2569	-0.1395	-0.9592***	-0.9872***	-0.2842	-0.0854***
	β				0.5400***			0.4972***			0.8030***	-0.0201**	0.7981***						1.0184***
	Number of lags	0	2	0	2	0	2	0	4	0	2	0	5	0	3	0	2	0	2
Oporto	ω	0.0044***	0.0003***	0.0212***	0.0116***	0.0111***	0.0126***	0.0198***	0.0146***	0.0270***	0.0091***	0.0133***	0.0111***	0.0000	0.0004	0.0053***	0.0056***	0.0027***	0.0025***
	α	0.5047***	-0.0548***	0.1094	-0.1532***	0.2079	-0.0297	0.6404***	0.2250**	0.6153	0.0414	1.7847***	1.3359***	0.0250	0.0313	1.3173***	0.8648***	0.5662**	0.2631
	γ	-0.1282	-0.0596*	0.46323	0.5659**	-0.0136	0.0037	-0.2433	0.0953	-0.3117	1.2881***	-1.1861**	-0.8561**	-0.0908**	0.0593	-1.0938**	-0.6866***	-0.4293	-0.2357
	β	-0.2146**	0.9974***		0.4676***			-0.1760**						1.0072***	0.9318***				
	Number of lags	0	2	0	3	0	1	0	7	0	6	0	3	0	3	0	2	0	2

Notes: ***denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; Others are non-specified countries; Lags are used in mean equation.

Source: author

Table 37 - LM tests for the TGARCH models applied to returns for all source markets and all cities

	Portugal		Brazil		France		Germany		Italy		Spain		UK		Others		Total	
	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL	No ARDL	ARDL
Coimbra	0.0014	2.2925	0.7720	1.0402	1.3293	0.2173	0.3063	0.0850	0.7813	0.0428	0.4257	11.8703***	0.8301	0.0525	0.0148	0.0232	0.0000	0.2562
Lisbon	0.0124	0.0017	0.3627	1.4707	0.3201	0.1364	0.8736	0.0059	0.0510	0.0346	3.0915*	4.1580**	0.2166	0.0177	0.0290	1.4272	0.7213	0.7842
Oporto	0.0447	1.8277	1.8883	0.5153	0.0606	0.0349	0.4137	0.0527	0.0004	0.0977	1.3173	1.2994	0.2140	0.0425	1.1116	0.5099	0.2692	0.0510

Note: ***denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; Others are non-specified countries.
Source: author

4.5. Evaluation of previous models

Table 38 summarizes all the models analysed in this thesis, taking into account the AIC, and rejecting models: with non-significant coefficients, models that do not satisfy the non-negativity constraints and models in which conditional heteroscedasticity was observed in residuals.

Table 38 - Summary of AIC for all models of returns from overnight stays from all source markets in all cities

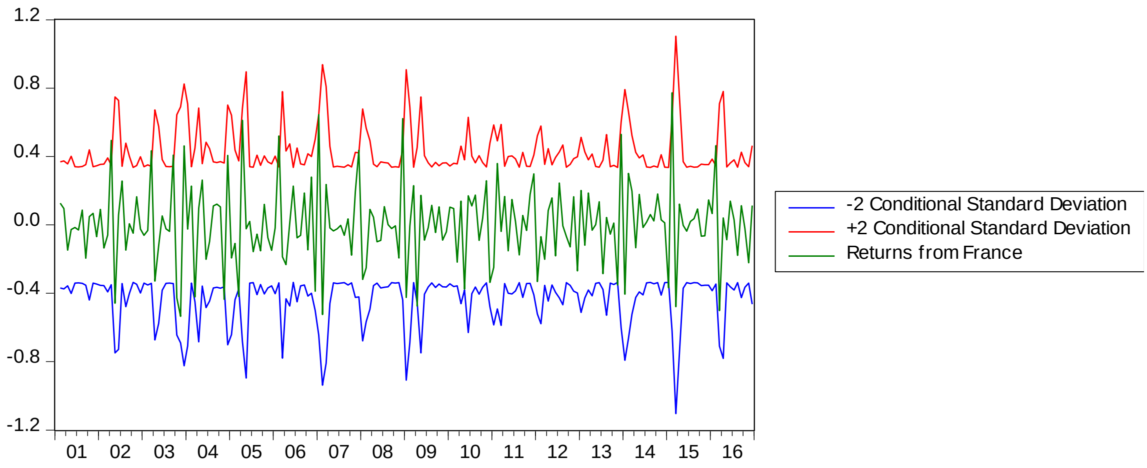
		GARCH		EGARCH		TGARCH	
		No ARDL	**ARDL**	**No ARDL**	**ARDL**	**No ARDL**	**ARDL**
Coimbra	**Portugal**	-1.9940	-2.1468	(a)	-2.1786	(a)	**-2.1836**
	Brazil	-0.1660	-0.2308	(a)	**-0.2579**	(a)	(a)
	France	**-0,2434**	(b)	(a)	(a)	(a)	(b)
	Germany	**-0.1550**	(b)	(a)	(a)	(a)	(b)
	Italy	**-0.0219**	(a)	(a)	(a)	(a)	(a)
	Spain	0.1265	-0.1506	(a)	**-0.1940**	0.0508	(c)
	UK	0.0685	**-0.1892**	(a)	-0.1887	(a)	(a)
	Others	**-0.8438**	(a)	(a)	(a)	(a)	(a)
	Total	-2.1848	-2.3788	(a)	-2.3898	(a)	**-2.3970**
Lisbon	**Portugal**	**-3.3038**	(a)	(a)	(a)	(a)	(a)
	Brazil	-1.3053	**-1.3766**	-1.3756	(a)	(a)	(b)
	France	-2.0364	-2.2316	(a)	**-2.2348**	(a)	(a)
	Germany	-1.8463	(a)	-1.8615	(a)	**-1.9895**	(a)
	Italy	**-1.4803**	(a)	(a)	(a)	(a)	(a)
	Spain	(c)	-0.8729	(a)	**-0.9883**	(c)	(c)
	UK	**-2.0035**	(a)	(a)	(a)	(a)	(a)
	Others	-2.8483	-2.8958	-2.8899	**-2.9570**	-2.9027	-2.9555
	Total	-3.0405	(a)	(a)	**-3.2481**	(a)	(a)
Oporto	**Portugal**	(b)	(b)	(a)	**-2.7494**	(a)	(b)
	Brazil	(c)	**-0.7931**	(a)	(a)	(a)	(b)
	France	**-1.4504**	(b)	(a)	(a)	(a)	(a)
	Germany	-0.8644	**-1.0895**	(a)	(a)	(a)	(a)
	Italy	-1.2823	-1.3063	**-1.3922**	(a)	(a)	(a)
	Spain	-0.5379	-0.9392	(a)	**-0.9999**	(c)	-0.9028
	UK	**-0.3634**	(a)	(a)	(a)	(a)	(a)
	Others	-1.7721	-1.8746	(a)	**-1.9240**	-1.7987	-1.8970
	Total	**-2.7734**	(a)	(a)	(a)	(a)	(a)

Notes: (a) non-significant coefficients; (b)non-negativity constraints failure; (c) conditional heteroscedastic residuals; Others are non-specified countries**.**

Source: author

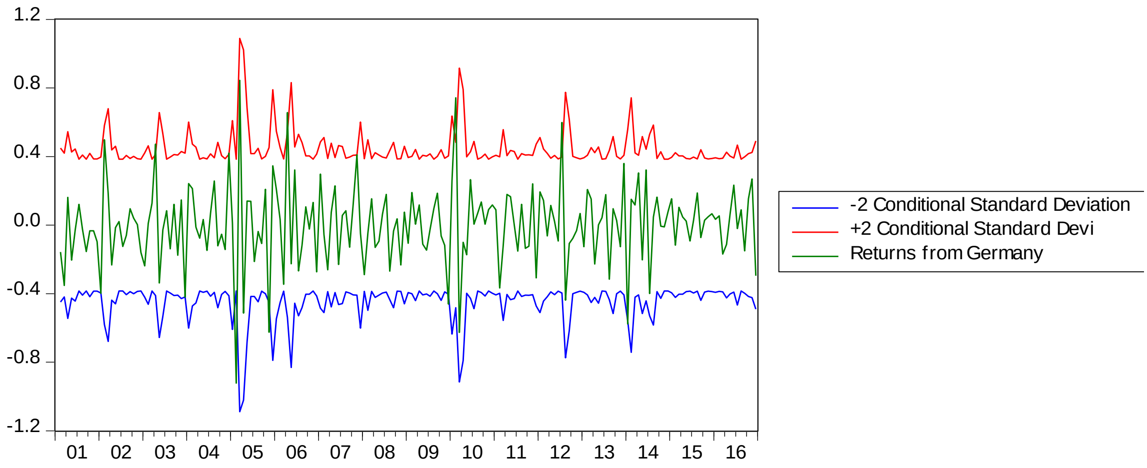
It can be verified that, in Coimbra, the ARCH(1) models, with no lags, are the most suitable for the returns from overnight stays coming from France (Figure 54), Germany (Figure 55), Italy (Figure 56) and non-specified countries (Figure 57).

Figure 54 - Data ± 2 standard deviations, ARCH(1) model for returns from France in Coimbra



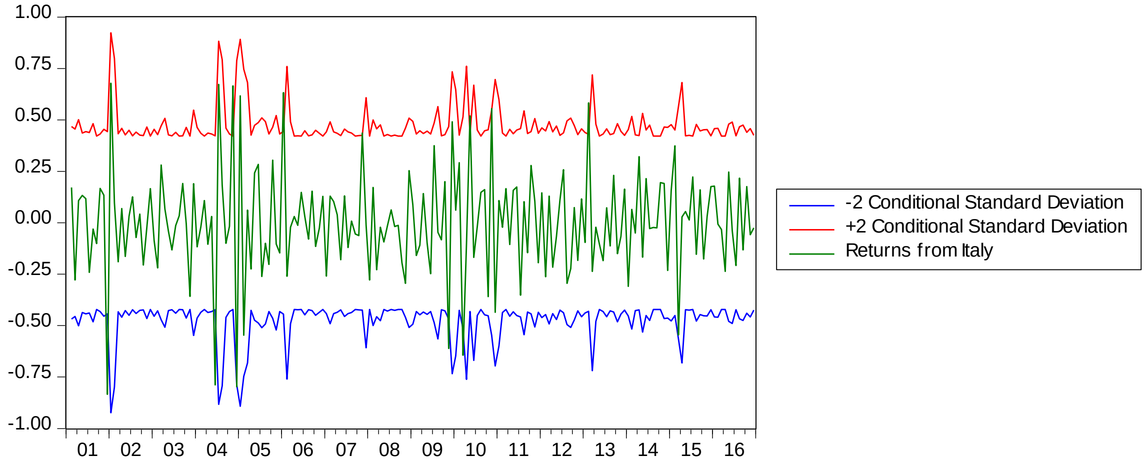
Source: author

Figure 55 - Data ± 2 standard deviations, ARCH(1) model for returns from Germany in Coimbra



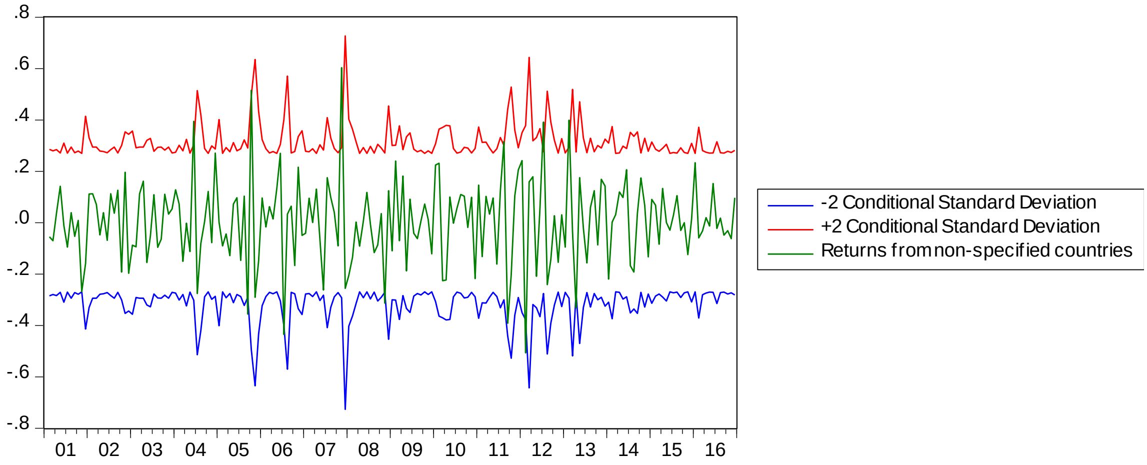
Source: author

Figure 56 - Data ± 2 standard deviations, ARCH(1) model for returns from Italy in Coimbra



Source: author

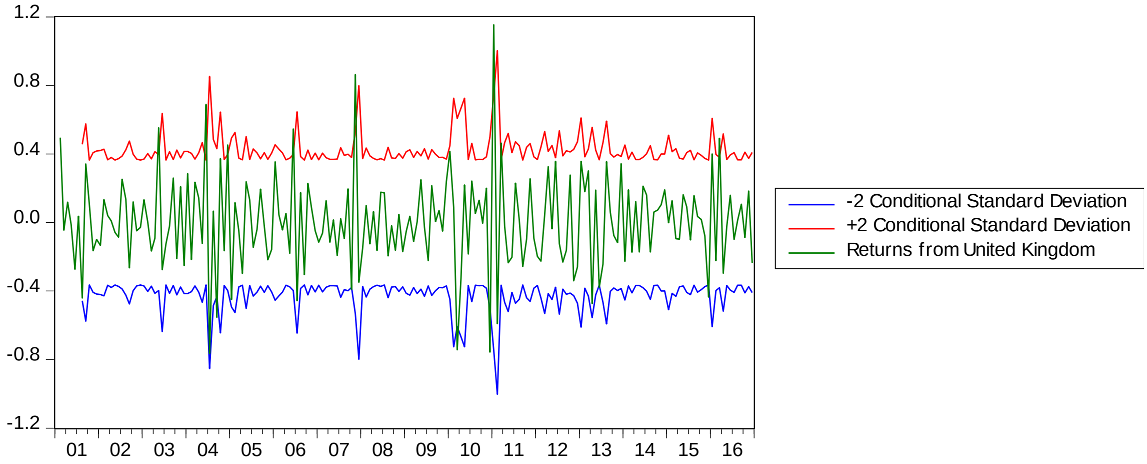
Figure 57 - Data ± 2 standard deviations, ARCH(1) model for returns from non-specified countries in Coimbra



Source: author

An ARCH(1), with six-time lags, is the most adequate model for returns from the United Kingdom (Figure 58).

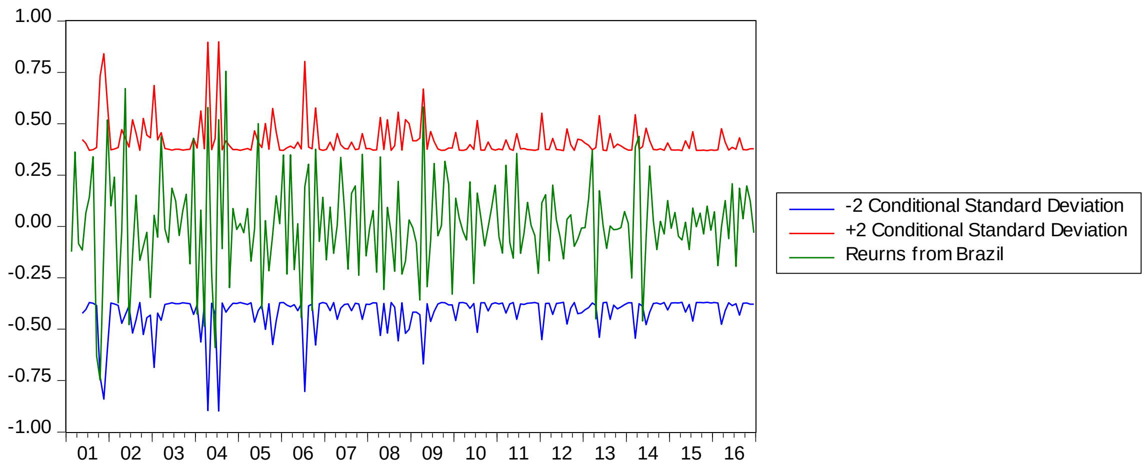
Figure 58 - Data ± 2 standard deviations, ARCH(1) model for returns from the United Kingdom in Coimbra



Source: author

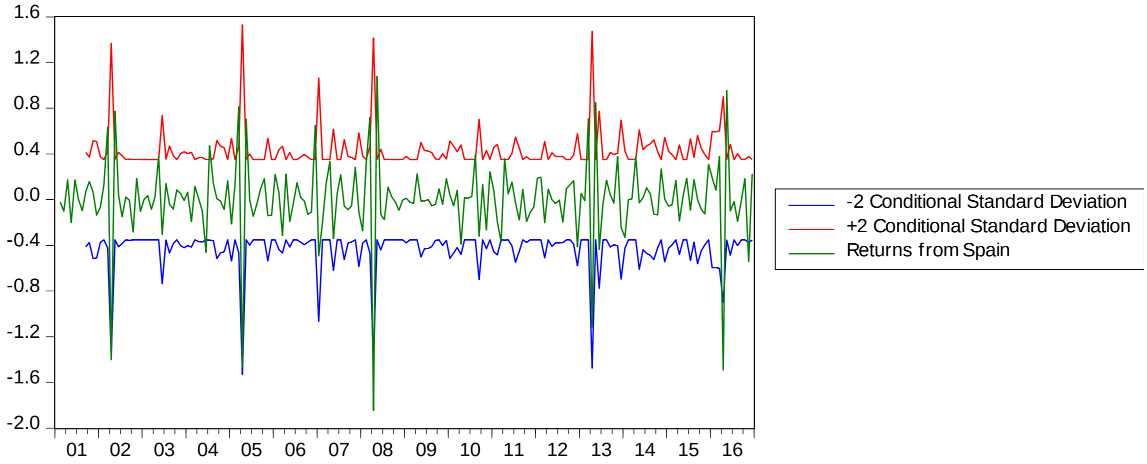
For returns from Brazil (Figure 59) and Spain (Figure 60) the most appropriate models are EGARCH(1,0), with three and seven lags, respectively, and in which a decrease in tourism demand causes an increase in volatility's persistence, for Brazil, and on the contrary, for Spain.

Figure 59 - Data ± 2 standard deviations, EGARCH(1,0) model for returns from Brazil in Coimbra



Source: author

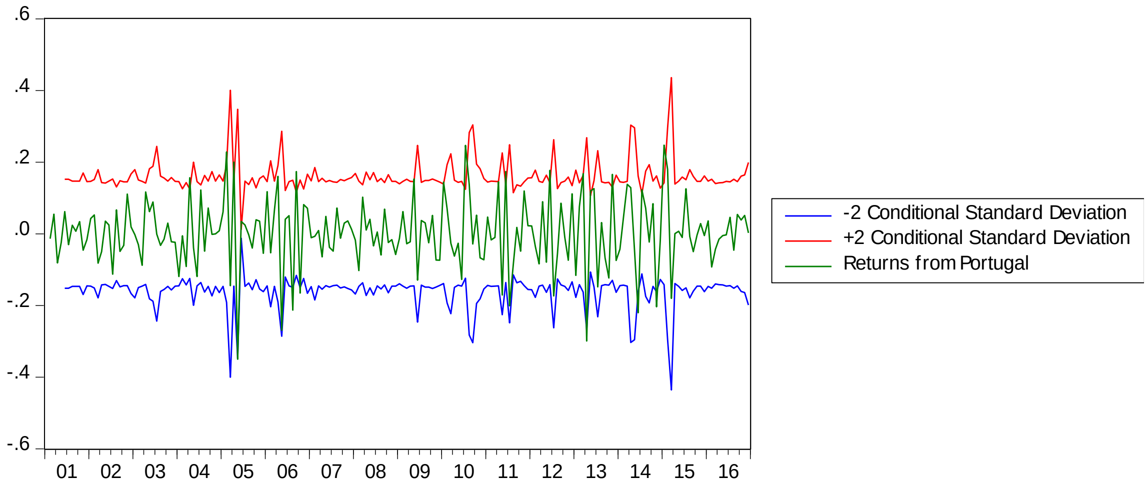
Figure 60 - Data ± 2 standard deviations, EGARCH(1,0) model for returns from Spain in Coimbra



Source: author

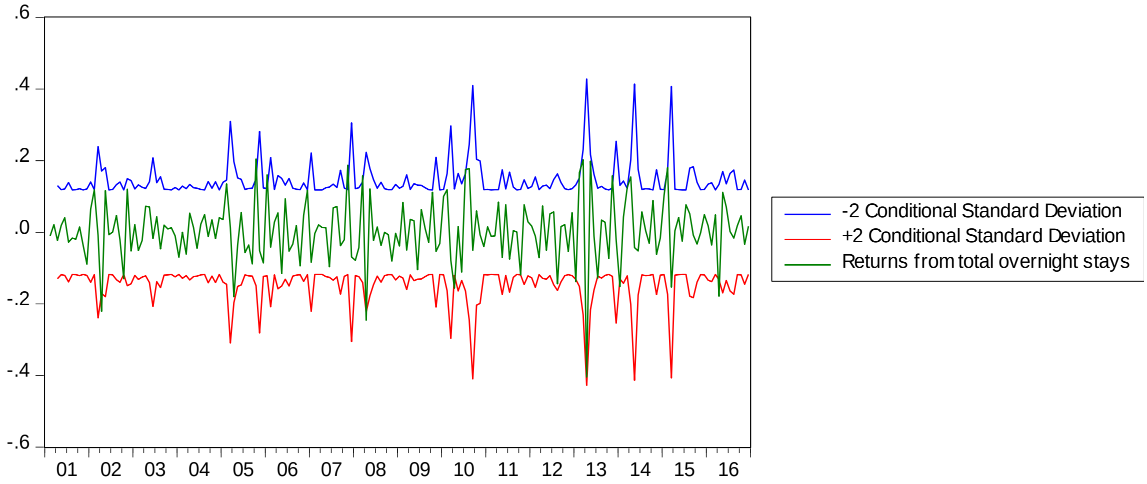
Finally, for returns from overnight stays from Portugal (Figure 61) and total overnight stays (Figure 62), the TARCH(1,0) models appear to be the most statistically adequate, with similar type of asymmetry to the Spanish model.

Figure 61 - Data ± 2 standard deviations, TARCH(1,0) model for returns from Portugal in Coimbra



Source: author

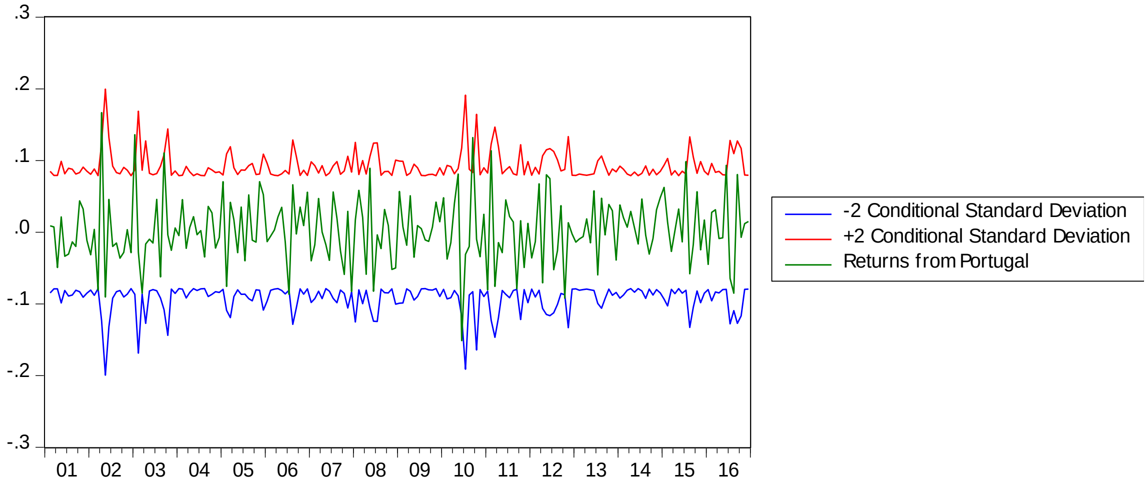
Figure 62 - Data ± 2 standard deviations, TARCH(1,0) model for returns from total overnight stays in Coimbra



Source: author

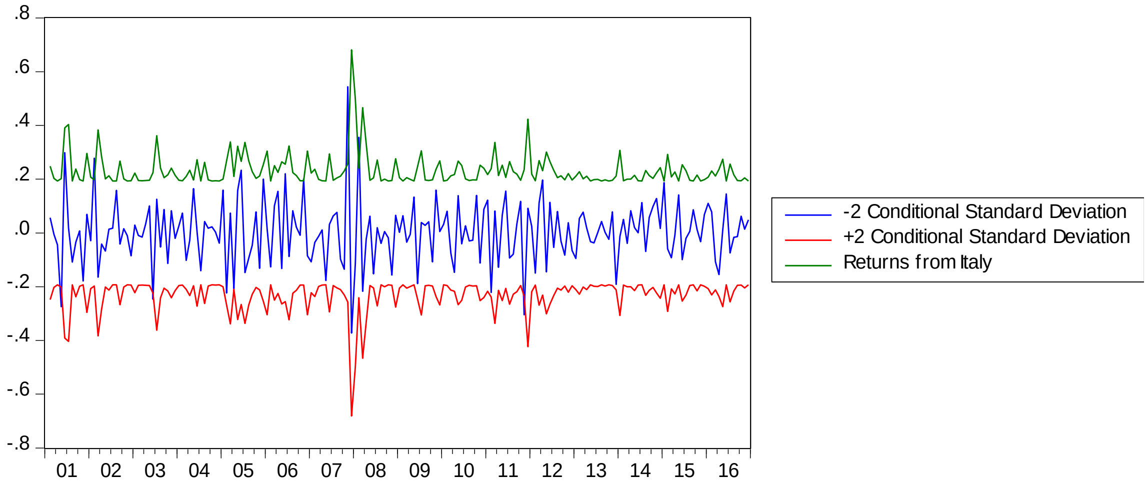
In Lisbon, ARCH(1) models without lags are the most appropriate for returns from Portugal (Figure 63), Italy (Figure 64), as in Coimbra, and the United Kingdom (Figure 65).

Figure 63 - Data ± 2 standard deviations, ARCH(1) model for returns from Portugal in Lisbon



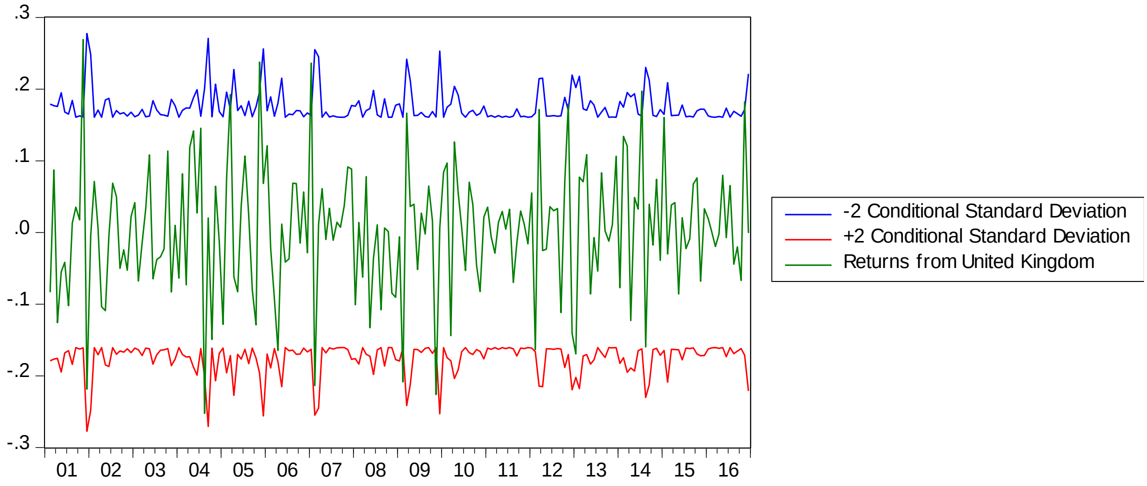
Source: author

Figure 64 - Data ± 2 standard deviations, ARCH(1) model for returns from Italy in Lisbon



Source: author

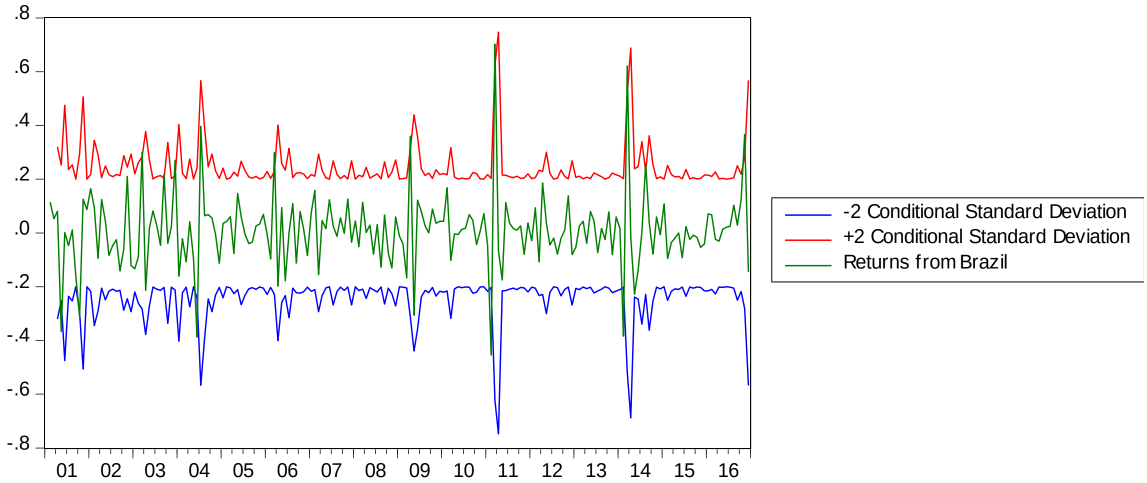
Figure 65 - Data ± 2 standard deviations, ARCH(1) model for returns from the United Kingdom in Lisbon



Source: author

Also, an ARCH(1) model, but with two lags, is shown to be the most apt for returns from overnight stays from Brazil (Figure 66).

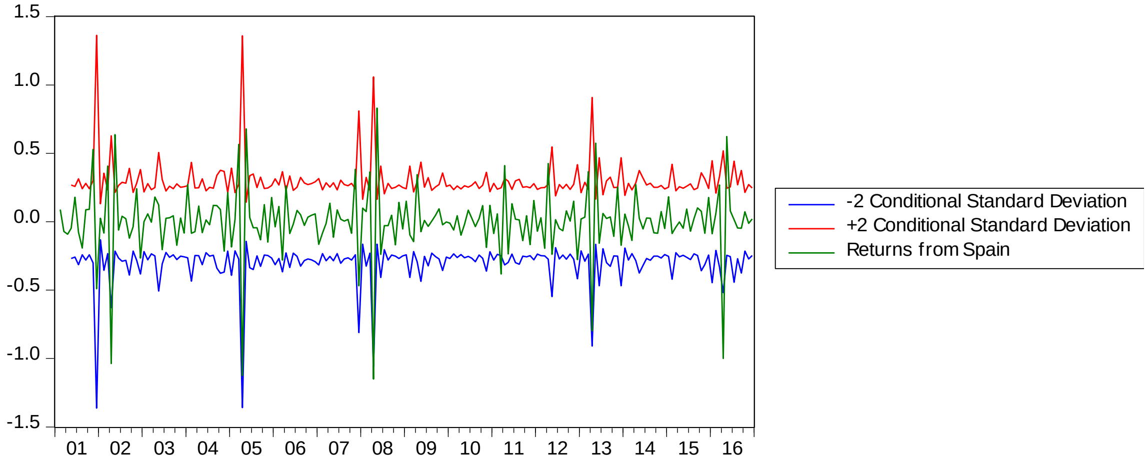
Figure 66 - Data ± 2 standard deviations, ARCH(1) model for returns from Brazil in Lisbon



Source: author

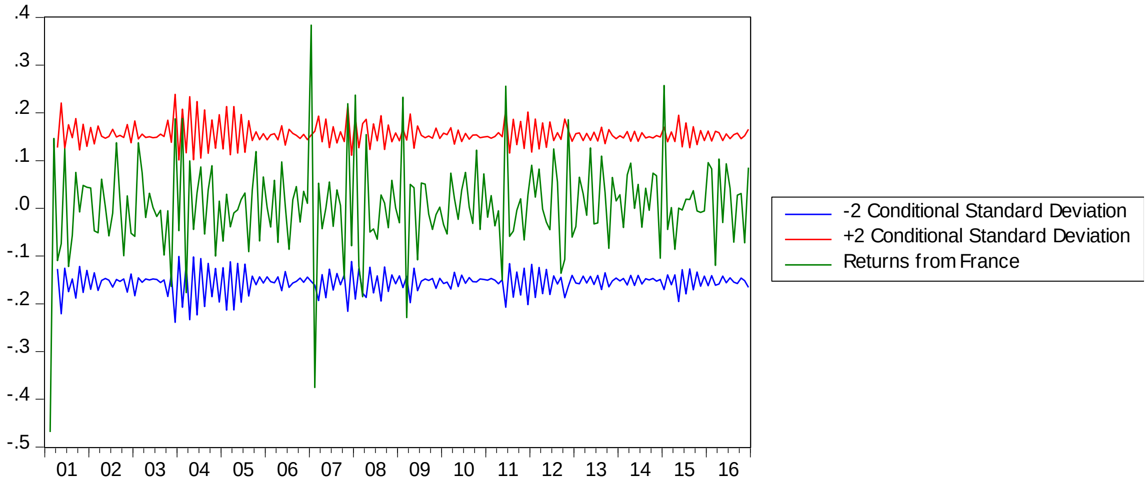
An EGARCH(1,1) model is the most suitable for the returns from Spain (Figure 67), as in Coimbra, but in this case with GARCH component, only with three lags and with the same type of asymmetry. Models of this type were also suitable for the returns from France (Figure 68), with two lags and with opposite asymmetry, non-specified countries (Figure 69), with two lags, and total overnight stays (Figure 70), without GARCH component and two lags.

Figure 67 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from Spain in Lisbon



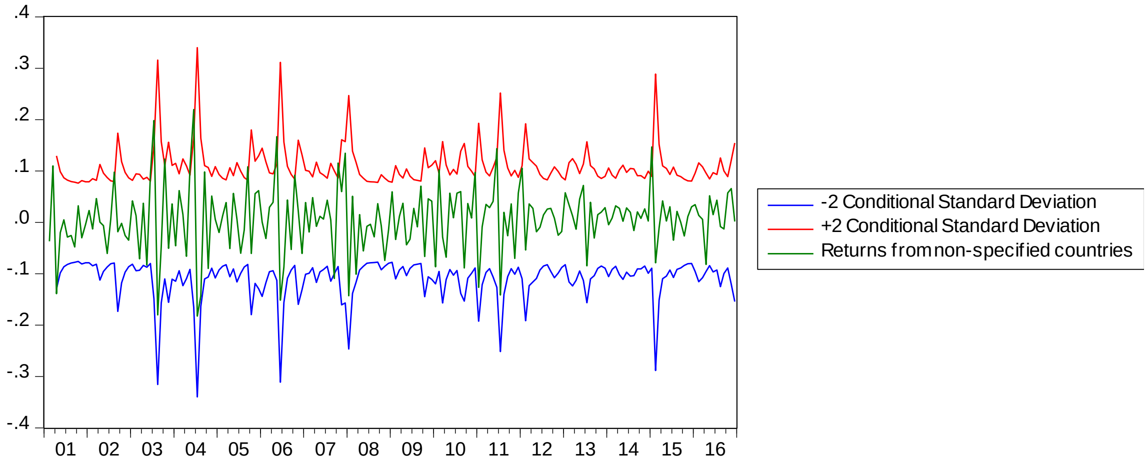
Source: author

Figure 68 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from France in Lisbon



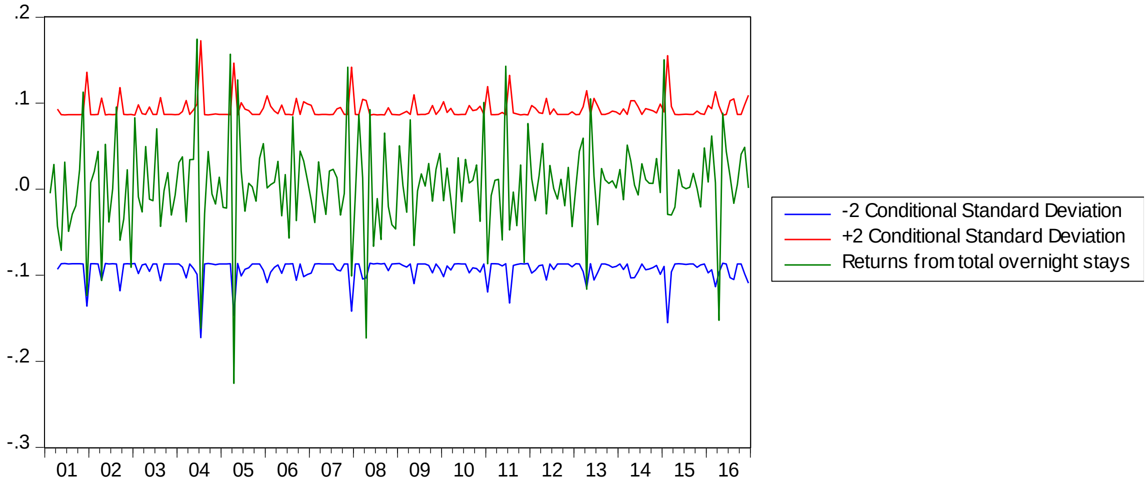
Source: author

Figure 69 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from other countries in Lisbon



Source: author

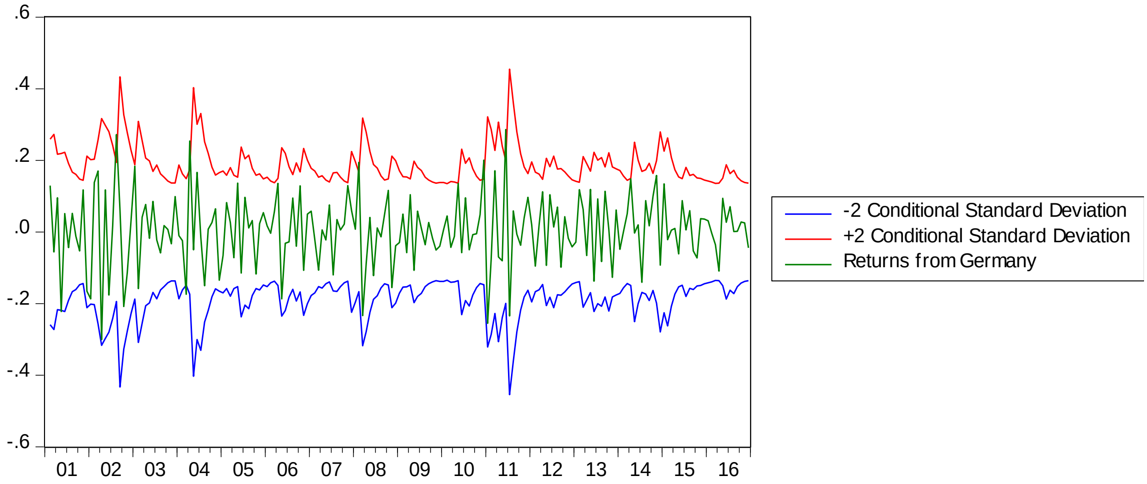
Figure 70 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from total overnight stays in Lisbon



Source: author

For returns from overnight stays from Germany (Figure 71), in Lisbon, the model that best fits data is a TGARCH(1,1) with no lags, non-finite memory and where the asymmetry parameter indicates that volatility increases with the decrease in tourism demand.

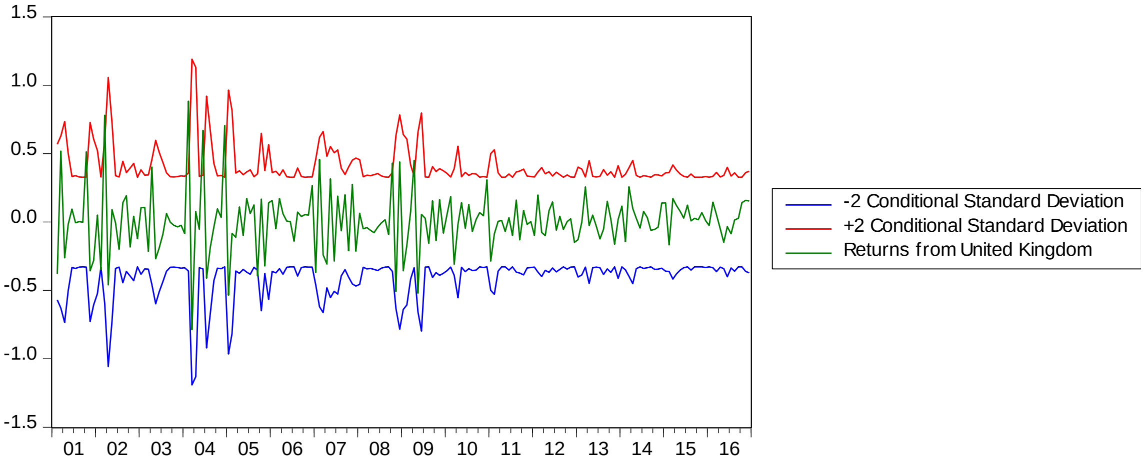
Figure 71 - Data ± 2 standard deviations, TGARCH(1,1) model for returns from Germany in Lisbon



Source: author

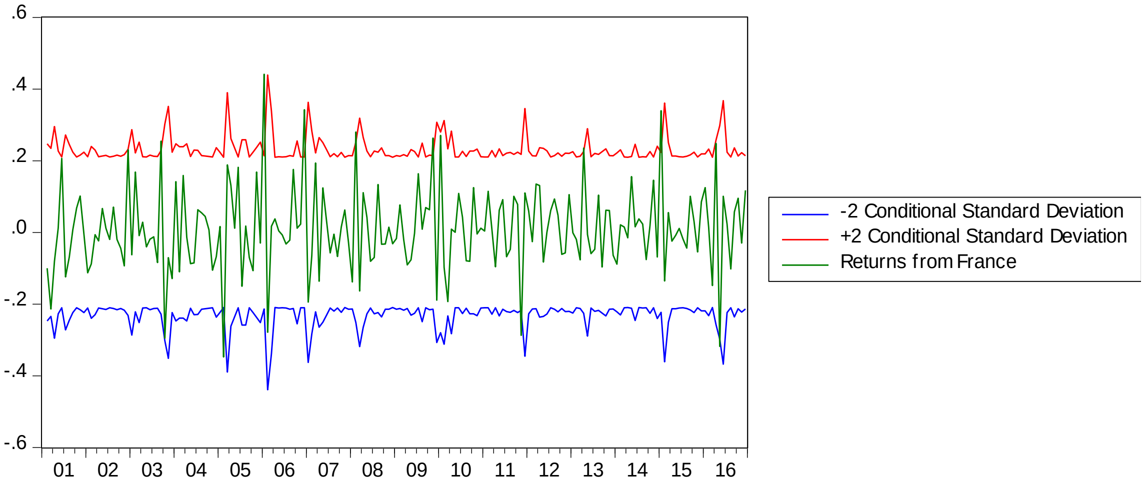
As in Lisbon, an ARCH(1) model without lags proved to be the best fit for returns from overnight stays from the United Kingdom, in Oporto (Figure 72). This type of model was also identified as the most suitable for returns from France, like in Coimbra, (Figure 73) and for total overnight stays (Figure 74) in this city.

Figure 72 - Data ± 2 standard deviations, ARCH(1) model for returns from the United Kingdom in Oporto



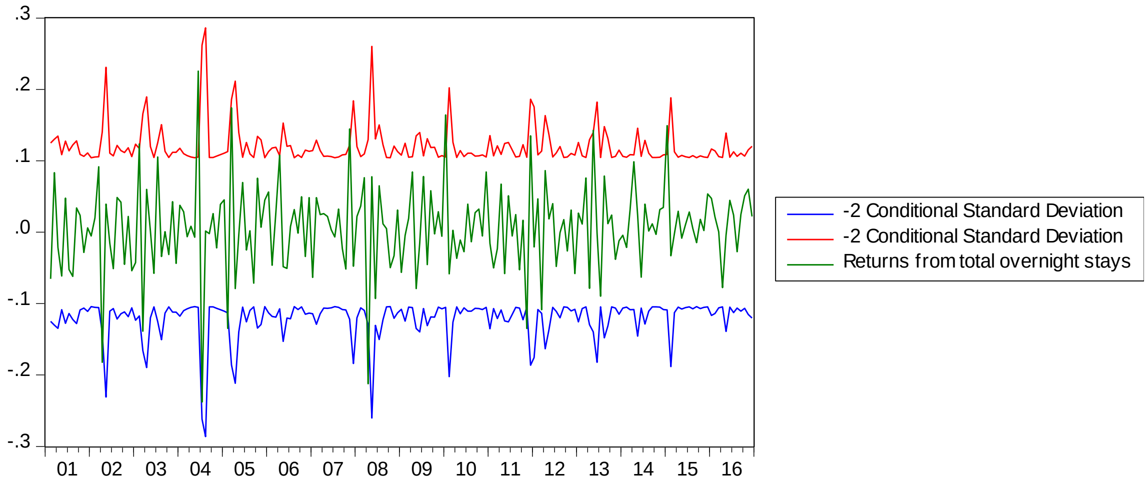
Source: author

Figure 73 - Data ± 2 standard deviations, ARCH(1) model for returns from France in Oporto



Source: author

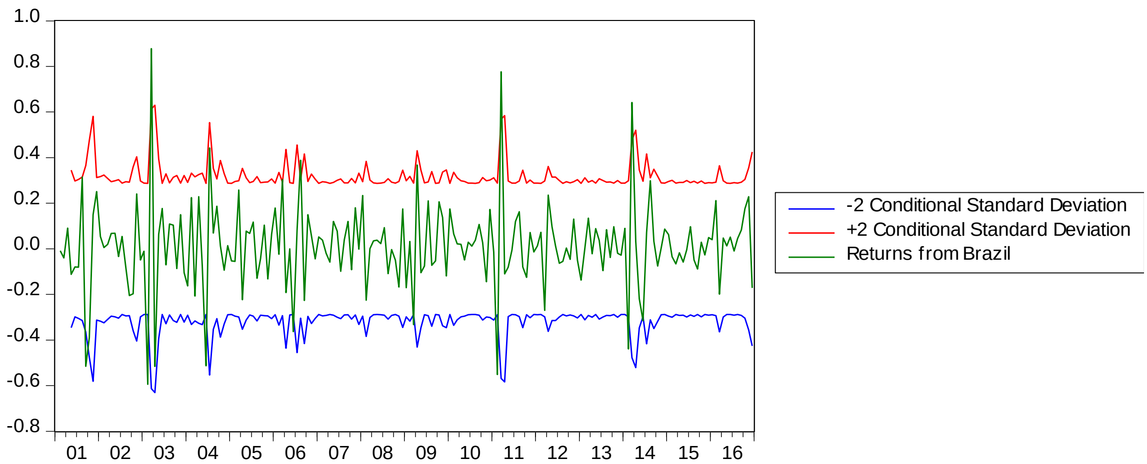
Figure 74 - Data ± 2 standard deviations, ARCH(1) model for returns from total overnight stays in Oporto



Source: author

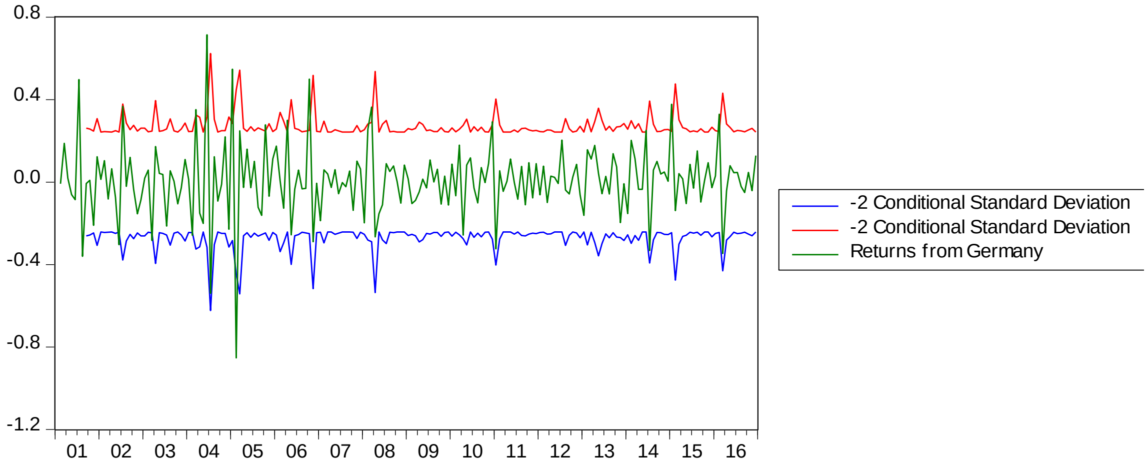
For returns from Brazil (Figure 75), as in Lisbon, and from Germany (Figure 76), the model that best fits data, in Oporto, is an ARCH(1), with three and seven lags, respectively.

Figure 75 - Data ± 2 standard deviations, ARCH(1) model for returns from Brazil in Oporto



Source: author

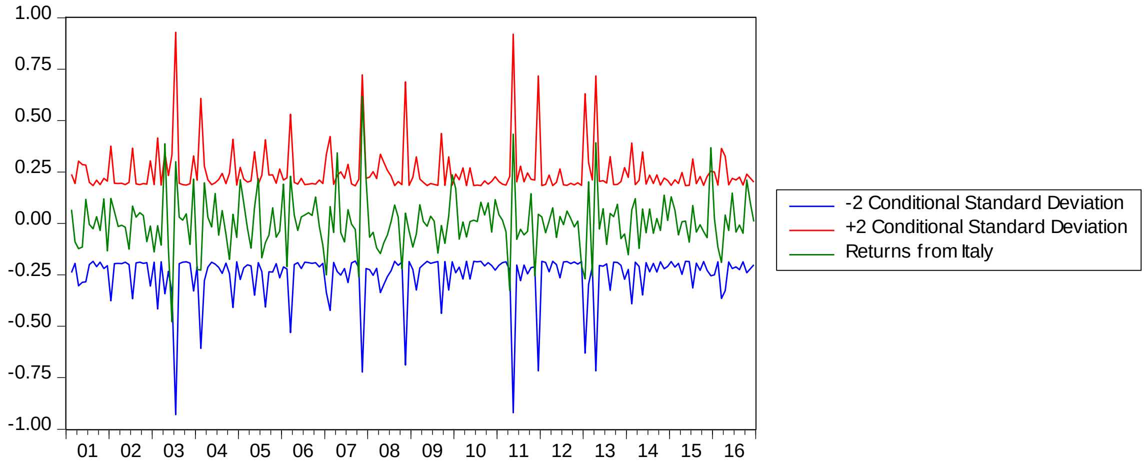
Figure 76 - Data ± 2 standard deviations, ARCH(1) model for returns from Germany in Oporto



Source: author

A non-lagged EGARCH(1,0) model proved to be the most suitable for returns from Italy (Figure 77), with negative asymmetry, i.e. volatility increases with decreasing tourism demand, in Oporto.

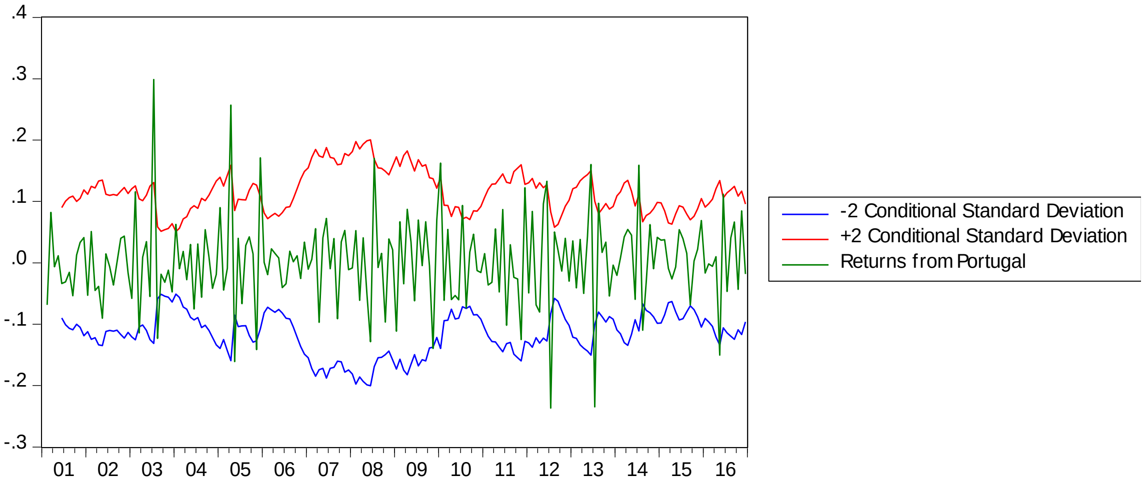
Figure 77 - Data ± 2 standard deviations, EGARCH(1,0) model for returns from Italy in Oporto



Source: author

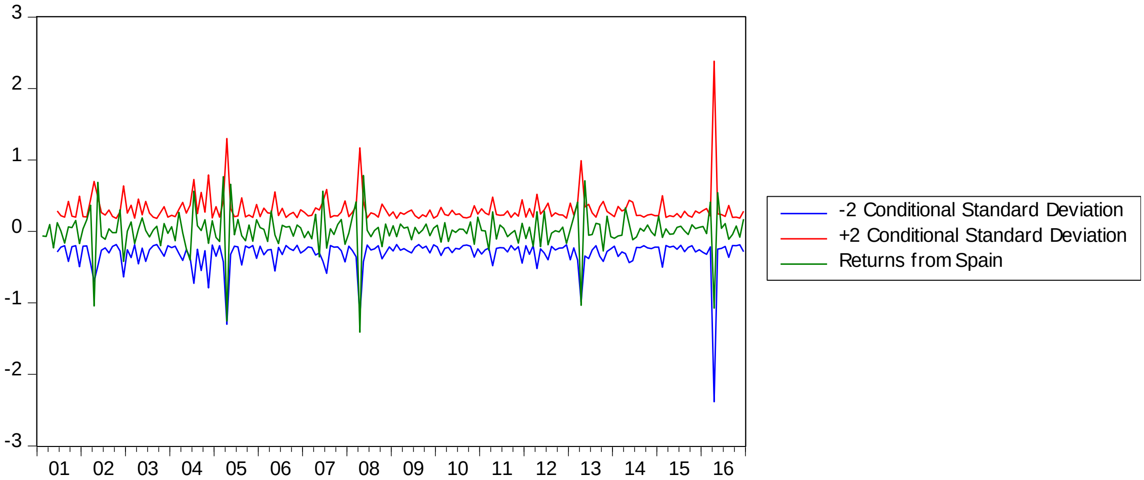
In this city, EGARCH models, with lags, for data from Portugal (Figure 78) with GARCH component and four lags, Spain (Figure 79) and non-specified countries (Figure 80), both without GARCH component, and with four and two lags, respectively, and the latter two having a positive asymmetry, that is, with volatility increasing with the increase in tourism demand, were identified as the more adjusted volatility models.

Figure 78 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from Portugal in Oporto



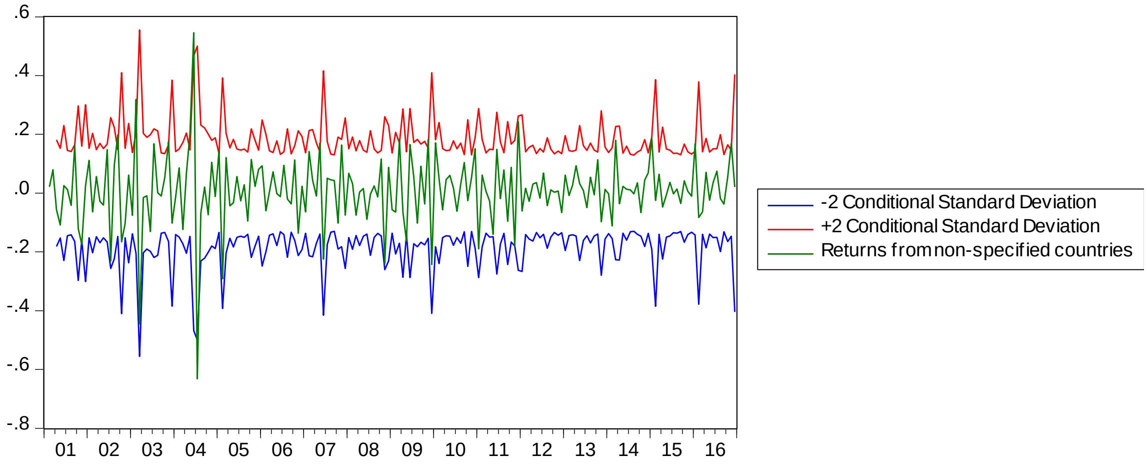
Source: author

Figure 79 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from Spain in Oporto



Source: author

Figure 80 - Data ± 2 standard deviations, EGARCH(1,1) model for returns from other countries in Oporto



Source: author

The persistence of volatility in the face of occasional events and the magnitude of bad news and good news, in models with asymmetry, are presented in Table 39.

The domestic market presents volatility with different behaviour in the three analysed cities. In Coimbra returns of overnight stays from the domestic market show volatility with positive asymmetry (that increases with the increase in tourism demand), while in Oporto we have volatility with negative asymmetry and in Lisbon there are no differences between good and bad news. Persistence is greater in Oporto and similar in the other two cities, being inferior in Coimbra.

The Brazilian market shows a symmetrical volatility of the returns of the overnight stays in face of positive and negative events, in Lisbon and Oporto, being in Lisbon that the persistence is greater. In Coimbra this market has an asymmetric volatility.

For the returns from overnight stays from France, in Coimbra and in Oporto, a symmetric model is the chosen, whereas a negative asymmetric model is the most adequate in the city of Lisbon.

In Coimbra and Oporto, returns from overnight stays from Germany show the same behaviour in face of the increase and decrease of tourism demand, both models being symmetrical. In Lisbon, the most suitable model for this source market is a negative asymmetric model, where the decrease in demand increases the volatility. It is also in this city that the persistence is greater.

Returns from overnight stays, in Coimbra and Lisbon, from Italy show the same behaviour in face of growth and reduction of tourism demand, with both models being symmetrical. In Oporto, the most appropriate model for this source market is a negative asymmetric model, where bad news increase volatility. Besides this, is in this city that the persistence is lesser.

The returns from overnight stays from Spain show a similar behaviour in the three cities: an asymmetric model proved to be the most adequate in all three situations, always with positive asymmetry, that is, with volatility increasing with increasing tourism demand. The persistence of the news is practically non-existent.

Also, for the three cities, the model for returns from overnight stays from the United Kingdom is similar, being a symmetrical model, with no differences to good and bad news. The persistence does not present significant differences, being the smaller one in the city of Lisbon and the greater one in the Oporto city.

For the returns of overnight stays coming from all other non-specified countries, the models are similar for the cities of Lisbon and Oporto, presenting positive symmetry. In Coimbra, for these countries, volatility model is symmetrical. Persistence has the highest value in the city of Lisbon and the lowest in Oporto.

In Lisbon and Oporto, returns from total overnight stays show a positive asymmetry in volatility, while in Coimbra a symmetric model is more adequate. In this last city, persistence has its higher value, and the lowest persistence occurs in Lisbon.

In Coimbra, volatility is more persistent for data from France and less persistent for data from Spain and Brazil. Only four models are asymmetric, three with positive asymmetry (data from domestic tourism, from Spain and total data) and one with negative asymmetry (Brazil). Among the first three, the one that presents greater magnitude in the face of good news is the Spanish market.

In Lisbon, there are three positive asymmetric volatility models: for the returns from Spain, unspecified countries and the total of overnight stays, being the one with the greatest magnitude in face of good news, the model of volatility for unspecified countries. There are also two models with negative asymmetric volatility, namely for returns from France and Germany, with similar magnitudes. For the other source markets volatility models are symmetrical. The model with the highest persistence of volatility is the one obtained for data from Germany, while the model that has the least persistence refers to France.

Finally, in the city of Oporto, there are two models of volatility with positive asymmetry, for data from Spain and non-specified countries, with similar magnitudes. There are also two models of volatility with negative asymmetry for returns from overnight stays from Portugal and Italy, the latter having the greatest magnitude. All other source markets present symmetric volatility models. The market that presents greater persistence is the domestic market and the one that displays less value of persistence is the market coming from non-specified countries.

Table 39 - Persistence and magnitude of news impact for all cities and source markets

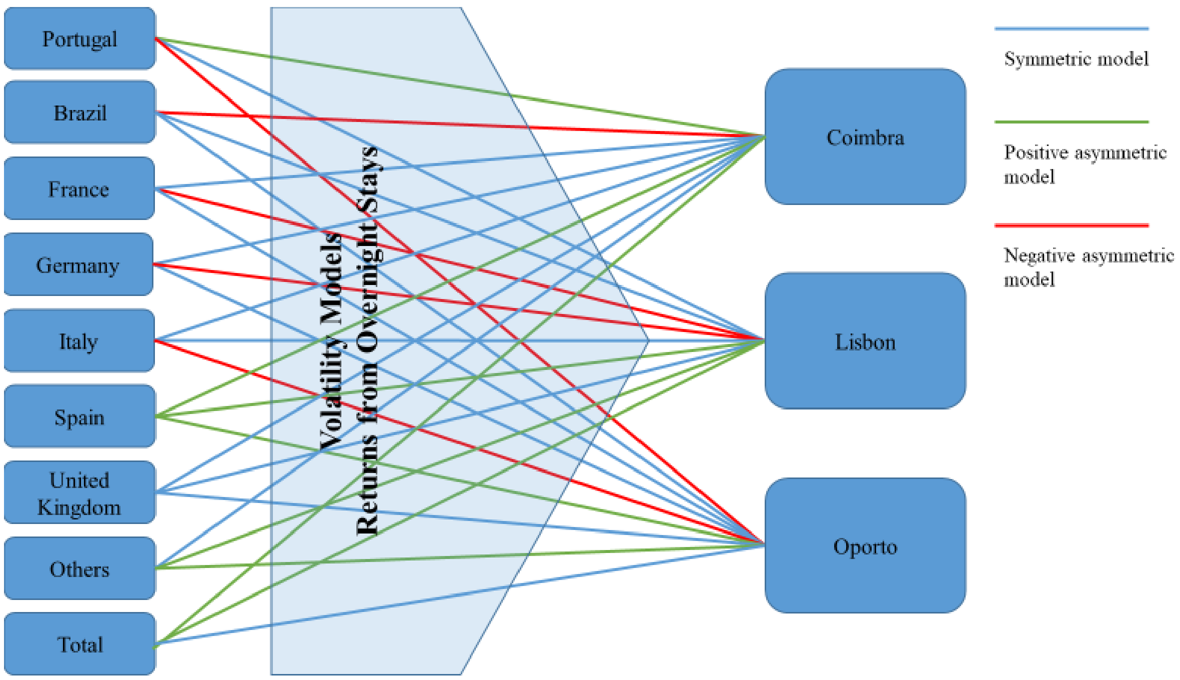
		Persistence	Magnitude	
			Bad News	Good News
Coimbra	Portugal	0.2235	-0.076	0,5229
	Brazil	0.0000	1.3061	0.6939
	France	0.4751	No asymmetry	
	Germany	0.3094	No asymmetry	
	Italy	0.2459	No asymmetry	
	Spain	0.0000	0.5966	1,4034
	UK	0.3126	No asymmetry	
	Others	0.3221	No asymmetry	
	Total	0.4368	0.1338	0,7398
Lisbon	Portugal	0.3164	No asymmetry	
	Brazil	0.4213	No asymmetry	
	France	-0.8472	1.1263	0,8737
	Germany	1.3656	1.1326	0,6042
	Italy	0.3683	No asymmetry	
	Spain	-0.3632	0.6464	1,3536
	UK	0.1816	No asymmetry	
	Others	0.5030	0.5908	1,4092
	Total	0.0000	0.8218	1,1782
Oporto	Portugal	0.8535	1.0678	0,9322
	Brazil	0.2167	No asymmetry	
	France	0.2050	No asymmetry	
	Germany	0.2530	No asymmetry	
	Italy	0.0000	1.4650	0,5350
	Spain	0.0000	0.7759	1,2241
	UK	0.4442	No asymmetry	
	Others	0.0000	0.8156	1,1844
	Total	0.2991	No asymmetry	

Note: Others are non-specified countries.

Source: author

Visually, the different models for volatility of returns from overnight stays in the three cities from all source markets may be analysed through Figure 81.

Figure 81 - Symmetry of volatility models in Coimbra, Lisbon and Oporto from all source markets



Source: author

Among the 27 city/origin pairs analysed, 52% of the volatility models presented symmetry in face of positive and negative shocks. Within the asymmetric models 62% presented positive asymmetry and the remaining (five models) revealed negative asymmetry.

5. Conclusions

5.1. Summary of Findings

The main motivations, described in the Introduction chapter of this thesis, were the growth of tourism at the international, European and, in particular, national levels. In these three measurement levels, there was a very solid growth of 81%, 60% and 76%, respectively, between 2001 and 2016, with Portugal growing above Europe.

Since 2015, Portugal has been in TOP15 of the most competitive countries in the world, with regard to travel and tourism. However, studies have only been carried out at a regional level, although the "city" product has been designated as a tourism resource in some of its regions.

The first objective of this research was fulfilled, since the systematic literature review allowed to prove the emerging need of using volatility models, mainly used with financial data, in the modelling of tourism demand, which also solved the first research question, as well as the identification of the most appropriate variables, data frequencies, temporal window and, above all, the most appropriate methodologies to reach good models.

The analysis of tourism demand in each of the three cities that were the object of study (Coimbra, Lisbon and Oporto) was carried out based on the main source markets including the domestic market (domestic tourism) that does not cross borders. So, tourism demand, was measured in overnight stays rather than arrivals. The arrivals would also make it impossible to associate tourism demand with each of the cities, although this is the most widely used variable in the literature.

The time window used in this research is in agreement with what is most current in the most recent literature, since the modal class is 10 to 15 years and, in this study, a time window of 16 years was used. The same happened with time frequency, as 46% of the most recent studies used monthly data. Despite the uncertainty associated with tourism demand, few studies have applied models of volatility, typical of financial analysis (only 12% of articles analysed in literature review for the last five years). However, the semantic analysis revealed the concept of volatility, linked to the analysis of growth in tourism, as an emerging theme.

This thesis examined volatilities of monthly returns of overnight stays, that is, the growth rate of monthly overnight stays, for three cities. Significance of correlation coefficient showed that in all cities there are complementary source markets as concerns to monthly overnight stays. However, monthly overnight stays and returns from overnight stays from different source markets to these three cities were examined separately because, statistically tests, revealed not to be necessary the use of cointegration analyses.

The state of the art has shown that it is important to model tourism demand disaggregated by source markets and at a lower regional level, and that it is important to test the accuracy of several models, in each tourism destination, and for each source market, since there is no model that is the perfect one for all situations. For Lisbon, Coimbra and Oporto, overnight stays from domestic tourism, Brazil, Germany, Italy, Spain and the United Kingdom, total overnight stays and data from other non-specified countries were employed to explore the existence of volatility in tourism demand.

In the tourism resource Coimbra, Turismo 2020, (Turismo de Portugal, 2015), presented three tourism offers: the City of Coimbra, and in this one the University classified as World Heritage Site by UNESCO, the Shanty Villages and Serra da Lousã and Figueira da Foz beaches, which can drive tourism demand in this city.

Four tourism offers have been indicated by Turismo 2020 for the tourism resource Lisbon: the Port of Lisbon Cruises, Docks and Marinas, Museums, Monuments and Congress Center, Gastronomy and Shopping and, finally, Activities and Events of Animation, Surf and Golf, which should continue to boost tourism demand in this city, that is considered a strong international brand, well positioned in city/short break, with a diversified offer complemented by the bordering counties (Turismo de Portugal, 2015).

The Turismo 2020 document indicated, in the tourism resource Oporto, also four tourism offers, namely, Culture and Knowledge, the Economic and Business Center, the Pole of Congresses, Conventions and Seminars and, finally, the Events of Animation, all with the capacity to enhance tourism demand in this city.

In the preliminary analysis of overnight stays data, anomalous values were identified and revised, in the time series from Brazil and Italy, in Coimbra, from Germany, in Coimbra and

Oporto, from the United Kingdom, in Coimbra, Lisbon and Oporto and from France in Lisbon, because volatility modelling is better when data are cleaned of outliers.

Coefficient of variation is quite high in all source markets and in cities, which indicates a large relative dispersion of data and slight representativeness of the mean. The returns from overnight stays from Germany, Spain and from total overnight stays have negative asymmetry in all cities analysed and all distributions are leptokurtic. The Jarque-Bera statistic allowed the rejection of the hypothesis of the returns having a normal distribution for all source markets at the usual levels of significance except for returns from Germany and the United Kingdom in Lisbon.

The markets that, preliminarily, indicated the existence of greater volatility were: for Coimbra, the Brazilian, the French (as in Oporto), the Italian (as in Lisbon) and the one from the United Kingdom (as in Oporto); for Lisbon, also the domestic market, the German and the one from non-specified countries; and, finally, for Oporto, also, from total overnight stays. Compared to the research from Daniel and Rodrigues (2010), for Portugal as a tourism destination, there are similarities in the French and German markets, which presented a larger evidence of volatility and in the Spanish market, that presented less evidence of volatility. Regarding domestic and United Kingdom source markets, the results were different, taking into account the destination Portugal or the three cities analysed in this research.

Unit root tests allowed to reject the hypothesis of non-stationarity in all the series of returns from overnight stays in the three cities analysed and individually ADF tests confirmed the fact of not being necessary the use of cointegration. The problem of heteroscedasticity with models with ARDL for returns from Brazil and Spain is common to the tree cities analysed in this thesis.

The second major objective of this research was to study tourism demand modelling in cities and this analysis was made through tourism demand volatility modelling. Six models, namely ARCH(1), GARCH(1,1), EGARCH(1,0), EGARCH(1,1), TARCH(1,0) and TGARCH(1,1), with and without lags, were used and compared to estimate the conditional volatility of returns from tourism demand in each of these cities. As in the studies of Daniel and Rodrigues (2010), Fernando et al. (2013), Liang (2014), Liu et al. (2014), Bunnag (2014, 2015), Tang et al. (2014), Balli et al. (2015), Balli and Tsui (2015) and Tang, Ramos, Cang and Sriboonchitta (2017), the analysed city tourism destinations revealed the existence of volatility in tourism demand.

The analysis of models with significant coefficients, that verified the non-negativity constraints and in which no conditional heteroscedastic residuals was verified, resulted in different models for different markets and cities, based on the AIC criterion.

The last objective of this research was to compare volatility of tourism demand between cities for the same source market and between source markets within each city. Only for returns from overnight stays from Spain and the United Kingdom, the models for the three cities were similar, namely, a symmetric model for the United Kingdom (ARCH model) and an asymmetric model for Spanish market (EGARCH model with lags).

The United Kingdom market was also analysed in terms of volatility in Thailand, with GARCH and TGARCH models, and the first one was also the better model according to AIC, like in the three cities analysed in this research. In this market, in the asymmetric model, just as in Coimbra an in Oporto (besides this model has not all coefficients statistically significant), volatility increases with decreasing in tourism demand (Bunnag, 2014). These results are also in agreement with those found for the five major Spanish tourism regions where symmetric and asymmetric models were identified, depending on the tourism destination (Bartolomé, McAller, Ramos, & Rey-Maquieira, 2007) and for Maldives (Shareef & McAleer, 2007)

Like in recent studies of Tiwari, Dash and Narayanan (2018) about 17 source markets in India and that from Croes and Ridderstaat (2017) in small islands destinations, the answer to the second research question is that there are, effectively, differences between the persistence of tourism demand volatility, in a specific city tourism destination, for different source markets and, also, between different city tourism destinations, for a specific source market.

More than half of the most suitable models are symmetrical models and among asymmetric models only five showed negative asymmetry, which, contrary to what happens with financial data, shows that, in relation to tourism demand, there are no different effects of good and bad news on volatility, or, else, it increases with the increase in demand (good news). This finding supports the studies of Shareef and McAleer (2007), that showed that asymmetries on tourism demand are not particularly intense and of Daniel and Rodrigues (2010), that suggested 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, in Portugal, with exception to time series from The Netherlands and Spain.

In Coimbra, the most suitable models were asymmetric models for markets from Portugal (as in Oporto), Brazil, Spain (as in Lisbon and Oporto) and for total overnight stays (as in Lisbon). In Lisbon, in addition to the aforementioned markets, asymmetries in returns from overnight stays from France, Germany and non-specified countries (such as Oporto) were, also, identified. In the latter, asymmetries were identified, in addition to those previously described, in the returns from Italy. Comparing with the analysis of Daniel and Rodrigues (2010), there are similarities in the conclusions related to the French, German and Spanish markets, where asymmetries were also identified, and also in the domestic and United Kingdom markets, where the symmetrical models were the most adequate.

This study allowed, also, to answer the third research question, so it can be said that there are differences between the persistence of tourism demand volatility for good and bad news in each of the cities, for the different source markets, and between the three city tourism destinations, for each specific source market as it was advanced by Assaf et al. (2012) in their research in Australia from about 30 source countries, and by Tsui and Balli (2015) in their research with tourist arrivals in eight different Australian airports.

As in the study of tourism demand volatility in Portugal (Daniel & Rodrigues, 2010), the persistence of shocks is small for overnight stays from Spain in the three cities as it occurred, also, in Australia (Assaf et al., 2012). However, the persistence is only high in Lisbon for overnight stays from Germany, as it happened in the study on Portugal but, in the other two cities, persistence is low in this source country.

In Coimbra, just one of the most suitable models for returns volatility presents negative asymmetry for returns of overnight stays from Brazil, while in Lisbon we have a negative asymmetry in the volatility of returns from overnight stays coming from France and Germany, and in Oporto from domestic tourism and Italy. In Lisbon there are only four symmetric volatility models for returns of overnights stays and in Oporto there are five. They are from Portugal and Italy, in Lisbon, from France, Germany and total overnight stays, in Oporto and from Brazil and the United Kingdom, in both cities.

As regards the last research question, it can be concluded that there are differences in the magnitude of the good news and bad news, in each city tourism destination, for different source markets, and in the three cities, for each source market, when there are differences in tourism demand volatility persistence, as it was identified previously in other destinations (Bunnag, 2014; C.-L. Chang et al., 2012).

The magnitude of tourism demand growth (good news) in Coimbra and Oporto is higher for the Spanish market and in Lisbon it is higher for non-specified countries. The magnitude of the decrease in tourism demand (bad news) in Lisbon is greater for the German market and, in Oporto, for the Italian market. The magnitude of the good news regarding the Spanish market is greater in Coimbra than in Oporto, with the non-specified countries market is higher in Lisbon than in Oporto and, finally, with regard to total overnight stays, the magnitude of good news is greater in Lisbon than in Coimbra.

5.2. Theoretical Contributions

The systematic literature review allowed the demonstration of the usefulness of semantic analysis tools, like Leximancer© (Version 4.5) software, in the identification of emerging themes, namely in the area of scientific production in tourism and, in particular, in the modelling tourism demand field. It also allowed the clarification of a different classification of the quantitative methods used in the analysis of tourism demand modelling, more specific than the usual classification that only dissociates methods into causal or non-causal, once different procedures were identified: time series models based on regression models, time series models based on volatility, time series models based on regression and volatility, time series forecasting models, structural models, neural networks, panel data and other non-specified quantitative models.

Since the studies that focus on the analysis of the volatility of tourism demand in Portugal are scarce, the development of this research, which was dedicated to the analysis and identification of different models of conditional volatility, intended to add empirical knowledge to this lacking reality.

In this research, a step toward working on the volatility modelling literature on Portuguese data was achieved. In addition to the different models of volatility in each city for each source market, different types of persistence of volatility in each market and city were found, and different magnitude in face of good news and bad news, which strengthens the need to adapt the modelling of tourism demand for each market and, within a country, at a more precise territorial scale.

These empirical results support the fact that an arbitrary selection of data frequency or spatial disaggregation will not lead to robust findings.

5.3. Managerial Implications

The modelling and analysis of volatility of returns from overnight stays in cities' major tourism source markets offers a valuable instrument for policy makers related to tourism and may contribute in the assessment of the impact in returns oscillations. A clear understanding of how volatility affects overnight stays from a specific source market in a specific city can help to an effective management and to allocate resources to deal with different patterns of tourists over time. The planning process of crisis and risk management has become the focal point of tourism destinations in order to moderate the negative impact of occurrences (Cakar, 2018).

According to Paraskevas, Altinay, McLean and Cooper (2013) there are three main stages of crisis management in tourism: the first is a post-crisis response and tries to moderate negative impacts, the second concentrates on the recovery and the third highlights on the pre-crisis. In this last stage both tourism stakeholders and hospitality organizations learn lessons in order to be prepared for future ones, involving models that offers a comprehensive knowledge of the past.

The type of models used in this thesis can be used in forecasting, to predict the existence or not, of future risks, namely, a high conditional variance. However, it is difficult to determine the accuracy of predictions, since volatility, measured in terms of conditional variance, is not directly observable.

Therefore, knowing the persistence, the type of asymmetry and magnitude of bad and good news for each source market and city, allows to articulate operative policy actions and may also prepare policy makers and private agents with information related to "how" and "when". Findings suggest that tourism industries should take into account the specific characteristics of individual source market in policies and plans.

The fact that Portugal is one of the safest countries in the world, based on an analysis carried out by the Institute for Economics and Peace, which annually publishes the Global Peace Index, and where Portugal ranks third position in 2017, out of a total of 163 countries, and the second position in Europe countries, can also lead to an increase in volatility of returns of tourism demand in our country, especially in cities, given that, between 2014 and 2016, the percentage of the population reporting terrorism as one of the most important issues in the European Union has tripled, associated to terrorist occurrences on cities on this continent (Institute for Economics and Peace, 2017). In Europe, Portugal experienced an improvement, between 2005 and 2015, in the positive pillar Acceptance of the Rights of Others, what can also provide positive changes in tourism demand.

For the stakeholders, it is important the diagnosis that in Coimbra, a reduction in demand on the part of the Brazilian market is reflected in an increase in volatility, but for the total overnight stays, domestic tourism and the Spanish market, the opposite happens, that is, good news increase volatility of tourism demand. In Lisbon, a reduction in tourism demand in the German and French markets is also reflected in an increase in tourism demand volatility, while for the total of overnight stays, those from non-specified countries and the Spanish market, it is the good news that increases the volatility of tourism demand.

Finally, for stakeholders related to the city of Oporto, it is also important to recognize that a decline in tourism demand by the domestic and Italian markets (although the latter is not one of the main inbound markets) causes an increase in the volatility of tourism demand. On the other hand, the increase in tourism demand by the Spanish market and that from non-specified countries is responsible for an increase in the volatility of tourism demand in this city. Data and evidence-based research will be key to understanding and respond effectively and efficiently to the challenges of the future. Data-driven decisions can help control source markets by supporting planning and decision-making processes (UNWTO, 2014).

When tourism managers are well aware of the volatility of tourism demand, they can adopt strategies that can gain from positive effects or avoid losses resulting from negative effects. It is also important to know whether negative impacts have permanent or temporary effects, to adapt stronger measures that allow recovery to the initial levels in the case of being permanent.

5.4. Limitations and Avenues for Future Research

Overnight stays do not include unpaid overnights from those who stays in their friends' homes, or those who have a second home. Also excluded from this research are the same-day visitors, who do not overnight stay in cities analysed, for more than 24 hours. These are limitations of this study, since, this kind of visitor may be usual in cities, namely in events and congresses.

The data provided by Statistics Portugal relate to the municipality where each city is included, since it is not possible to distinguish among those who overnight stay in the municipality, who are looking for the tourism product 'city' or other tourism product.

The use of other autoregressive conditional heteroscedastic models, like Asymmetric Power Autoregressive Conditional Heteroscedastic (APARCH), Integrated Generalized Autoregressive Conditional Heteroscedastic (IGARCH), Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroscedastic (FIEGARCH), Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroscedastic (FIAPARCH) including causal ones, using other variables, such as data from search engines, can be a way to improve modelling of volatility of the returns in tourism demand. Research using the multivariate Autoregressive Conditional Heteroscedastic models, like ARCH/GARCH-M and FIEGARCH-M, also may be added to this one.

An extension of this research may include more data, when available, that might have a significant impact on tourism demand, such as tourism marketing expenditure. This research can be extended, also, to emerging source markets with the objective of analysing a specific tourism policy, using dummy variables, which make it possible to measure the weight of these policies in the returns of tourism demand.

The study of tourism demand volatility by market segments can also be an important avenue for future research to reveal emerging market niches in each of the cities.

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Appendices

Appendix A – EViews outputs with descriptive statistics for returns from overnight stays in Coimbra, Lisbon and Oporto

Sample: 2001M01 2016M12

	RCB_BRAZI...	RCB_FRAN...	RCB_GERM...	RCB_ITALY...	RCB_OTHE...	RCB_PORT...	RCB_SPAIN...	RCB_TOTA...	RCB_UK_SA
Mean	0.010582	0.002887	-0.000923	0.000119	0.004136	0.002364	0.001382	0.003045	0.003128
Median	-0.002367	-0.004813	0.005268	-0.014509	0.006004	-0.002997	2.28E-05	0.000366	-0.004013
Maximum	0.754814	0.772404	0.844881	0.678522	0.602806	0.247107	1.078821	0.204397	1.153871
Minimum	-0.746935	-0.535421	-0.922011	-0.834079	-0.506366	-0.350034	-1.844632	-0.404218	-0.764290
Std. Dev.	0.237659	0.230641	0.233956	0.248254	0.162017	0.096354	0.348492	0.085637	0.264508
Skewness	0.066720	0.271583	-0.052659	-0.152216	0.104057	-0.334027	-1.477458	-0.479054	0.344213
Kurtosis	3.887218	3.838122	5.201298	4.706908	4.251943	4.112701	11.40695	5.438894	5.152438
Jarque-Bera	6.406164	7.938248	38.65207	23.92444	12.81827	13.40501	631.9581	54.64329	40.64257
Probability	0.040637	0.018890	0.000000	0.000006	0.001646	0.001228	0.000000	0.000000	0.000000
Sum	2.021096	0.551476	-0.176294	0.022748	0.790071	0.451503	0.263874	0.581512	0.597370
Sum Sq. Dev.	10.73153	10.10715	10.39974	11.70973	4.987433	1.763965	23.07489	1.393387	13.29323
Observations	191	191	191	191	191	191	191	191	191

Sample: 2001M01 2016M12

	RLX_BRAZI...	RLX_FRAN...	RLX_GERM...	RLX_ITALY_SA	RLX_OTHE...	RLX_PORT...	RLX_SPAIN...	RLX_TOTAL...	RLX_UK_SA
Mean	0.008606	0.006056	0.004335	0.003112	0.005851	0.002329	0.001967	0.004458	0.003437
Median	0.012701	0.001891	0.007610	0.005256	0.008499	-0.002478	0.015000	0.005608	0.006658
Maximum	0.702187	0.383848	0.285753	0.543777	0.219131	0.166577	0.831413	0.174418	0.269028
Minimum	-0.454539	-0.468619	-0.300363	-0.371932	-0.182402	-0.151275	-1.149973	-0.225613	-0.252369
Std. Dev.	0.139406	0.096401	0.098782	0.118493	0.063615	0.047207	0.251155	0.055261	0.089113
Skewness	0.791748	-0.366887	-0.189441	0.340198	-0.066376	0.244198	-1.202941	-0.328412	-0.046164
Kurtosis	8.567874	7.655197	3.491541	5.237419	4.202113	3.846679	10.10103	5.657079	3.574608
Jarque-Bera	266.6732	176.7489	3.065263	43.52398	11.64065	7.603366	447.3604	59.61975	2.695481
Probability	0.000000	0.000000	0.215967	0.000000	0.002967	0.022333	0.000000	0.000000	0.259827
Sum	1.643702	1.156633	0.827992	0.594443	1.117449	0.444808	0.375778	0.851508	0.656384
Sum Sq. Dev.	3.692470	1.765685	1.854014	2.667694	0.768903	0.423415	11.98501	0.580226	1.508807
Observations	191	191	191	191	191	191	191	191	191

Sample: 2001M01 2016M12

	ROP_BRAZI...	ROP_FRAN...	ROP_GERM...	ROP_ITALY...	ROP_OTHE...	ROP_PORT...	ROP_SPAIN...	ROP_TOTA...	ROP_UK_SA
Mean	0.010403	0.009281	0.007650	0.004683	0.008558	0.002426	0.006638	0.005988	0.006713
Median	0.012840	0.003417	0.006550	-0.003450	0.010920	0.001073	0.014854	0.005995	0.006258
Maximum	0.878354	0.441289	0.714008	0.618220	0.545887	0.298674	0.783432	0.225479	0.883755
Minimum	-0.593693	-0.347281	-0.852682	-0.478468	-0.631790	-0.236569	-1.408128	-0.237738	-0.787019
Std. Dev.	0.189942	0.118294	0.175940	0.135994	0.118516	0.072311	0.272116	0.062429	0.220666
Skewness	0.388153	0.267828	-0.098767	0.629354	-0.655386	0.251178	-1.550823	-0.239426	0.437020
Kurtosis	7.357663	4.382075	7.363949	6.086588	9.486139	5.371303	11.72852	5.350286	5.920924
Jarque-Bera	155.9187	17.48493	151.8695	88.42799	348.4804	46.75872	682.8823	45.78544	73.97858
Probability	0.000000	0.000160	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.987046	1.772641	1.461097	0.894543	1.634603	0.463289	1.267949	1.143728	1.282153
Sum Sq. Dev.	6.854820	2.658755	5.881438	3.513913	2.668736	0.993485	14.06900	0.740505	9.251744
Observations	191	191	191	191	191	191	191	191	191

Appendix B – EViews outputs with correlations between overnight returns from each of the source markets in Coimbra, Lisbon and Oporto

Covariance Analysis: Ordinary

Sample: 2001M02 2016M12
Included observations: 191
Balanced sample (listwise missing value deletion)

Correlation t-Statistic Probability	RCB_BRAZI...	RCB_FRAN...	RCB_GERM...	RCB_ITALY...	RCB_OTHE...	RCB_PORT...	RCB_SPAIN...	RCB_TOTA...	RCB_UK_SA
RCB_BRAZIL_SA	1.000000								

RCB_FRANCE_SA	-0.075345	1.000000							
	-1.038778	-----							
	0.3002	-----							
RCB_GERMANY_SA	0.021477	0.033994	1.000000						
	0.295325	0.467614	-----						
	0.7681	0.6406	-----						
RCB_ITALY_SA	0.137096	0.048445	0.195512	1.000000					
	1.902729	0.666792	2.740740	-----					
	0.0586	0.5057	0.0067	-----					
RCB_OTHERS_SA	0.018782	0.100497	0.400432	0.239222	1.000000				
	0.258249	1.388642	6.007712	3.387101	-----				
	0.7965	0.1666	0.0000	0.0009	-----				
RCB_PORTUGAL...	0.223770	0.083143	-0.035364	0.076742	0.059837	1.000000			
	3.156367	1.146995	-0.486478	1.058154	0.824098	-----			
	0.0019	0.2528	0.6272	0.2913	0.4109	-----			
RCB_SPAIN_SA	0.040247	-0.220400	0.196949	0.086102	0.100389	0.065766	1.000000		
	0.553760	-3.106380	2.761686	1.188115	1.387133	0.906091	-----		
	0.5804	0.0022	0.0063	0.2363	0.1670	0.3660	-----		
RCB_TOTAL_SA	0.235783	0.031130	0.278353	0.287152	0.487495	0.624446	0.596710	1.000000	
	3.335517	0.428175	3.984176	4.121254	7.675818	10.99098	10.22286	-----	
	0.0010	0.6690	0.0001	0.0001	0.0000	0.0000	0.0000	-----	
RCB_UK_SA	-0.091911	-0.003616	0.177222	0.063376	0.406431	0.023504	0.107786	0.271764	1.000000
	-1.268939	-0.049717	2.475588	0.873032	6.115377	0.323215	1.490502	3.882252	-----
	0.2060	0.9604	0.0142	0.3838	0.0000	0.7469	0.1378	0.0001	-----

Covariance Analysis: Ordinary

Sample: 2001M02 2016M12
Included observations: 191
Balanced sample (listwise missing value deletion)

Correlation t-Statistic Probability	RLX_BRAZI...	RLX_FRAN...	RLX_GERM...	RLX_ITALY...	RLX_OTHE...	RLX_PORT...	RLX_SPAIN...	RLX_TOTAL...	RLX_UK_SA
RLX_BRAZIL_SA	1.000000								

RLX_FRANCE_SA	0.097395	1.000000							
	1.345350	-----							
	0.1801	-----							
RLX_GERMANY_SA	0.186790	0.144320	1.000000						
	2.613948	2.005066	-----						
	0.0097	0.0464	-----						
RLX_ITALY_SA	0.095219	0.184868	0.205620	1.000000					
	1.315019	2.586089	2.888527	-----					
	0.1901	0.0105	0.0043	-----					
RLX_OTHERS_SA	0.008834	0.144067	0.291548	0.189767	1.000000				
	0.121454	2.001474	4.190155	2.657145	-----				
	0.9035	0.0468	0.0000	0.0086	-----				
RLX_PORTUGAL_...	-0.032364	0.026960	-0.059352	0.205827	0.098897	1.000000			
	-0.445170	0.370769	-0.817398	2.891571	1.366314	-----			
	0.6567	0.7112	0.4147	0.0043	0.1735	-----			
RLX_SPAIN_SA	0.026021	0.006315	0.273864	0.225676	0.032782	0.019201	1.000000		
	0.357855	0.086824	3.914678	3.184695	0.450920	0.264017	-----		
	0.7209	0.9309	0.0001	0.0017	0.6526	0.7921	-----		
RLX_TOTAL_SA	0.132463	0.190179	0.503991	0.462236	0.504700	0.285171	0.706878	1.000000	
	1.837253	2.663128	8.022075	7.166224	8.037196	4.090296	13.73882	-----	
	0.0677	0.0084	0.0000	0.0000	0.0000	0.0001	0.0000	-----	
RLX_UK_SA	0.032210	0.182373	0.170755	0.026110	0.227489	0.074808	-0.004370	0.189970	1.000000
	0.443041	2.549972	2.382488	0.359075	3.211671	1.031331	-0.060085	2.660101	-----
	0.6582	0.0116	0.0182	0.7199	0.0016	0.3037	0.9522	0.0085	-----

Covariance Analysis: Ordinary

Sample: 2001M02 2016M12
Included observations: 191
Balanced sample (listwise missing value deletion)

Correlation t-Statistic Probability	ROP_BRAZI...	ROP_FRAN...	ROP_GERM...	ROP_ITALY...	ROP_OTHE...	ROP_PORT...	ROP_SPAIN...	ROP_TOTA...	ROP_UK_SA
ROP_BRAZIL_SA	1.000000								

ROP_FRANCE_SA	-0.056057	1.000000							
	-0.771869	-----							
	0.4412	-----							
ROP_GERMANY_SA	-0.171669	0.139606	1.000000						
	-2.395619	1.938248	-----						
	0.0176	0.0541	-----						
ROP_ITALYL_SA	-0.068645	0.211296	0.219623	1.000000					
	-0.945942	2.971945	3.094878	-----					
	0.3454	0.0033	0.0023	-----					
ROP_OTHERS_SA	-0.178926	0.188480	0.413002	0.186046	1.000000				
	-2.500177	2.638459	6.234388	2.603152	-----				
	0.0133	0.0090	0.0000	0.0100	-----				
ROP_PORTUGAL...	0.005793	0.142066	-0.036184	0.098993	0.090302	1.000000			
	0.079642	1.973104	-0.497775	1.367645	1.246535	-----			
	0.9366	0.0499	0.6192	0.1730	0.2141	-----			
ROP_SPAIN_SA	0.064988	-0.076621	0.052975	-0.039893	-0.130969	-0.066756	1.000000		
	0.895327	-1.056467	0.729315	-0.548879	-1.816176	-0.919796	-----		
	0.3718	0.2921	0.4667	0.5837	0.0709	0.3589	-----		
ROP_TOTAL_SA	-0.021570	0.210510	0.413557	0.248817	0.611703	0.347866	0.453939	1.000000	
	-0.296614	2.960366	6.244486	3.531741	10.63032	5.100946	7.003823	-----	
	0.7671	0.0035	0.0000	0.0005	0.0000	0.0000	0.0000	-----	
ROP_UK_SA	0.022477	-0.010123	0.082943	0.015499	0.443311	0.052367	-0.014051	0.440331	1.000000
	0.309084	-0.139174	1.144225	0.213105	6.799134	0.720915	-0.193192	6.742392	-----
	0.7576	0.8895	0.2540	0.8315	0.0000	0.4719	0.8470	0.0000	-----

Appendix C - EViews outputs with group unit root tests for Coimbra, Lisbon and Oporto

Group unit root test: Summary
Series: RCB_BRAZIL_SA, RCB_FRANCE_SA, RCB_GERMANY_SA,
RCB_ITALY_SA, RCB_OTHERS_SA, RCB_PORTUGAL_SA,
RCB_SPAIN_SA, RCB_TOTAL_SA, RCB_UK_SA

Sample: 2001M01 2016M12
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 1 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-34.0627	0.0000	9	1693
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-40.7867	0.0000	9	1693
ADF - Fisher Chi-square	869.325	0.0000	9	1693
PP - Fisher Chi-square	220.844	0.0000	9	1710

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Group unit root test: Summary
Series: RLX_BRAZIL_SA, RLX_FRANCE_SA, RLX_GERMANY_SA,
RLX_ITALY_SA, RLX_OTHERS_SA, RLX_PORTUGAL_SA,
RLX_SPAIN_SA, RLX_TOTAL_SA, RLX_UK_SA

Sample: 2001M01 2016M12
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 1 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-36.8754	0.0000	9	1697
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-43.6889	0.0000	9	1697
ADF - Fisher Chi-square	903.333	0.0000	9	1697
PP - Fisher Chi-square	654.519	0.0000	9	1710

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Group unit root test: Summary
Series: ROP_BRAZIL_SA, ROP_FRANCE_SA, ROP_GERMANY_SA,
ROP_ITALYL_SA, ROP_OTHERS_SA, ROP_PORTUGAL_SA,
ROP_SPAIN_SA, ROP_TOTAL_SA, ROP_UK_SA

Sample: 2001M01 2016M12
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-51.1087	0.0000	9	1701
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-50.5198	0.0000	9	1701
ADF - Fisher Chi-square	925.627	0.0000	9	1701
PP - Fisher Chi-square	356.152	0.0000	9	1710

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Appendix D - EViews outputs with Granger causality tests in Coimbra, Lisbon and Oporto

Pairwise Granger Causality Tests

Sample: 2001M01 2016M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
RCB_FRANCE_SA does not Granger Cause RCB_BRAZIL_SA	189	1.64580	0.1957
RCB_BRAZIL_SA does not Granger Cause RCB_FRANCE_SA		0.78868	0.4560
RCB_GERMANY_SA does not Granger Cause RCB_BRAZIL_SA	189	0.79235	0.4543
RCB_BRAZIL_SA does not Granger Cause RCB_GERMANY_SA		1.29100	0.2775
RCB_ITALY_SA does not Granger Cause RCB_BRAZIL_SA	189	0.13113	0.8772
RCB_BRAZIL_SA does not Granger Cause RCB_ITALY_SA		0.48967	0.6136
RCB_OTHERS_SA does not Granger Cause RCB_BRAZIL_SA	189	0.53966	0.5839
RCB_BRAZIL_SA does not Granger Cause RCB_OTHERS_SA		4.27527	0.0153
RCB_PORTUGAL_SA does not Granger Cause RCB_BRAZIL_SA	189	0.54786	0.5791
RCB_BRAZIL_SA does not Granger Cause RCB_PORTUGAL_SA		0.85677	0.4262
RCB_SPAIN_SA does not Granger Cause RCB_BRAZIL_SA	189	0.13409	0.8746
RCB_BRAZIL_SA does not Granger Cause RCB_SPAIN_SA		0.67526	0.5103
RCB_TOTAL_SA does not Granger Cause RCB_BRAZIL_SA	189	0.20268	0.8167
RCB_BRAZIL_SA does not Granger Cause RCB_TOTAL_SA		0.28730	0.7506
RCB_UK_SA does not Granger Cause RCB_BRAZIL_SA	189	0.37448	0.6882
RCB_BRAZIL_SA does not Granger Cause RCB_UK_SA		0.43843	0.6457
RCB_GERMANY_SA does not Granger Cause RCB_FRANCE_SA	189	2.77858	0.0647
RCB_FRANCE_SA does not Granger Cause RCB_GERMANY_SA		0.20184	0.8174
RCB_ITALY_SA does not Granger Cause RCB_FRANCE_SA	189	3.70283	0.0265
RCB_FRANCE_SA does not Granger Cause RCB_ITALY_SA		1.04277	0.3545
RCB_OTHERS_SA does not Granger Cause RCB_FRANCE_SA	189	2.31608	0.1015
RCB_FRANCE_SA does not Granger Cause RCB_OTHERS_SA		0.50673	0.6033
RCB_PORTUGAL_SA does not Granger Cause RCB_FRANCE_SA	189	0.61418	0.5422
RCB_FRANCE_SA does not Granger Cause RCB_PORTUGAL_SA		3.07342	0.0486
RCB_SPAIN_SA does not Granger Cause RCB_FRANCE_SA	189	2.38813	0.0946
RCB_FRANCE_SA does not Granger Cause RCB_SPAIN_SA		0.09644	0.9081
RCB_TOTAL_SA does not Granger Cause RCB_FRANCE_SA	189	1.95831	0.1440
RCB_FRANCE_SA does not Granger Cause RCB_TOTAL_SA		1.09649	0.3362
RCB_UK_SA does not Granger Cause RCB_FRANCE_SA	189	4.16661	0.0170
RCB_FRANCE_SA does not Granger Cause RCB_UK_SA		0.55641	0.5742
RCB_ITALY_SA does not Granger Cause RCB_GERMANY_SA	189	7.82413	0.0005
RCB_GERMANY_SA does not Granger Cause RCB_ITALY_SA		1.12753	0.3261
RCB_OTHERS_SA does not Granger Cause RCB_GERMANY_SA	189	1.22172	0.2971
RCB_GERMANY_SA does not Granger Cause RCB_OTHERS_SA		0.44643	0.6406

RCB_PORTUGAL_SA does not Granger Cause RCB_GERMANY_SA	189	1.96401	0.1432
RCB_GERMANY_SA does not Granger Cause RCB_PORTUGAL_SA		2.28155	0.1050
RCB_SPAIN_SA does not Granger Cause RCB_GERMANY_SA	189	0.63657	0.5303
RCB_GERMANY_SA does not Granger Cause RCB_SPAIN_SA		0.39078	0.6771
RCB_TOTAL_SA does not Granger Cause RCB_GERMANY_SA	189	1.87393	0.1564
RCB_GERMANY_SA does not Granger Cause RCB_TOTAL_SA		0.11861	0.8882
RCB_UK_SA does not Granger Cause RCB_GERMANY_SA	189	0.17894	0.8363
RCB_GERMANY_SA does not Granger Cause RCB_UK_SA		0.44465	0.6417
RCB_OTHERS_SA does not Granger Cause RCB_ITALY_SA	189	2.85461	0.0601
RCB_ITALY_SA does not Granger Cause RCB_OTHERS_SA		1.39683	0.2500
RCB_PORTUGAL_SA does not Granger Cause RCB_ITALY_SA	189	0.53649	0.5857
RCB_ITALY_SA does not Granger Cause RCB_PORTUGAL_SA		1.39574	0.2503
RCB_SPAIN_SA does not Granger Cause RCB_ITALY_SA	189	1.09958	0.3352
RCB_ITALY_SA does not Granger Cause RCB_SPAIN_SA		6.00257	0.0030
RCB_TOTAL_SA does not Granger Cause RCB_ITALY_SA	189	2.77908	0.0647
RCB_ITALY_SA does not Granger Cause RCB_TOTAL_SA		2.60773	0.0764
RCB_UK_SA does not Granger Cause RCB_ITALY_SA	189	1.78169	0.1712
RCB_ITALY_SA does not Granger Cause RCB_UK_SA		1.76128	0.1747
RCB_PORTUGAL_SA does not Granger Cause RCB_OTHERS_SA	189	1.42751	0.2426
RCB_OTHERS_SA does not Granger Cause RCB_PORTUGAL_SA		3.02160	0.0511
RCB_SPAIN_SA does not Granger Cause RCB_OTHERS_SA	189	0.31736	0.7285
RCB_OTHERS_SA does not Granger Cause RCB_SPAIN_SA		1.09639	0.3362
RCB_TOTAL_SA does not Granger Cause RCB_OTHERS_SA	189	0.29377	0.7458
RCB_OTHERS_SA does not Granger Cause RCB_TOTAL_SA		1.57217	0.2104
RCB_UK_SA does not Granger Cause RCB_OTHERS_SA	189	0.61274	0.5430
RCB_OTHERS_SA does not Granger Cause RCB_UK_SA		1.00448	0.3682
RCB_SPAIN_SA does not Granger Cause RCB_PORTUGAL_SA	189	0.14072	0.8688
RCB_PORTUGAL_SA does not Granger Cause RCB_SPAIN_SA		1.22091	0.2973
RCB_TOTAL_SA does not Granger Cause RCB_PORTUGAL_SA	189	1.84598	0.1608
RCB_PORTUGAL_SA does not Granger Cause RCB_TOTAL_SA		0.85520	0.4269
RCB_UK_SA does not Granger Cause RCB_PORTUGAL_SA	189	0.88441	0.4147
RCB_PORTUGAL_SA does not Granger Cause RCB_UK_SA		0.68719	0.5043
RCB_TOTAL_SA does not Granger Cause RCB_SPAIN_SA	189	2.23202	0.1102
RCB_SPAIN_SA does not Granger Cause RCB_TOTAL_SA		2.73615	0.0675
RCB_UK_SA does not Granger Cause RCB_SPAIN_SA	189	0.25920	0.7719
RCB_SPAIN_SA does not Granger Cause RCB_UK_SA		0.61477	0.5419
RCB_UK_SA does not Granger Cause RCB_TOTAL_SA	189	1.88385	0.1549
RCB_TOTAL_SA does not Granger Cause RCB_UK_SA		2.74546	0.0669

Pairwise Granger Causality Tests

Sample: 2001M01 2016M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
RLX_FRANCE_SA does not Granger Cause RLX_BRAZIL_SA	189	0.35810	0.6995
RLX_BRAZIL_SA does not Granger Cause RLX_FRANCE_SA		0.90127	0.4078
RLX_GERMANY_SA does not Granger Cause RLX_BRAZIL_SA	189	2.64705	0.0736
RLX_BRAZIL_SA does not Granger Cause RLX_GERMANY_SA		0.52266	0.5938
RLX_ITALY_SA does not Granger Cause RLX_BRAZIL_SA	189	1.31349	0.2714
RLX_BRAZIL_SA does not Granger Cause RLX_ITALY_SA		0.34034	0.7120
RLX_OTHERS_SA does not Granger Cause RLX_BRAZIL_SA	189	0.42603	0.6537
RLX_BRAZIL_SA does not Granger Cause RLX_OTHERS_SA		0.15099	0.8600
RLX_PORTUGAL_SA does not Granger Cause RLX_BRAZIL_SA	189	1.33415	0.2659
RLX_BRAZIL_SA does not Granger Cause RLX_PORTUGAL_SA		0.35946	0.6985
RLX_SPAIN_SA does not Granger Cause RLX_BRAZIL_SA	189	0.23920	0.7875
RLX_BRAZIL_SA does not Granger Cause RLX_SPAIN_SA		0.08492	0.9186
RLX_TOTAL_SA does not Granger Cause RLX_BRAZIL_SA	189	0.09651	0.9080
RLX_BRAZIL_SA does not Granger Cause RLX_TOTAL_SA		0.02963	0.9708
RLX_UK_SA does not Granger Cause RLX_BRAZIL_SA	189	0.20214	0.8172
RLX_BRAZIL_SA does not Granger Cause RLX_UK_SA		2.19941	0.1138
RLX_GERMANY_SA does not Granger Cause RLX_FRANCE_SA	189	0.81203	0.4455
RLX_FRANCE_SA does not Granger Cause RLX_GERMANY_SA		0.13089	0.8774
RLX_ITALY_SA does not Granger Cause RLX_FRANCE_SA	189	0.62744	0.5351
RLX_FRANCE_SA does not Granger Cause RLX_ITALY_SA		1.31301	0.2715
RLX_OTHERS_SA does not Granger Cause RLX_FRANCE_SA	189	3.73363	0.0257
RLX_FRANCE_SA does not Granger Cause RLX_OTHERS_SA		1.20767	0.3013
RLX_PORTUGAL_SA does not Granger Cause RLX_FRANCE_SA	189	0.34747	0.7069
RLX_FRANCE_SA does not Granger Cause RLX_PORTUGAL_SA		1.56195	0.2125
RLX_SPAIN_SA does not Granger Cause RLX_FRANCE_SA	189	0.09370	0.9106
RLX_FRANCE_SA does not Granger Cause RLX_SPAIN_SA		1.08660	0.3395
RLX_TOTAL_SA does not Granger Cause RLX_FRANCE_SA	189	1.39894	0.2495
RLX_FRANCE_SA does not Granger Cause RLX_TOTAL_SA		1.43833	0.2400
RLX_UK_SA does not Granger Cause RLX_FRANCE_SA	189	1.85319	0.1596
RLX_FRANCE_SA does not Granger Cause RLX_UK_SA		0.34279	0.7102
RLX_ITALY_SA does not Granger Cause RLX_GERMANY_SA	189	0.25489	0.7753
RLX_GERMANY_SA does not Granger Cause RLX_ITALY_SA		0.37369	0.6887
RLX_OTHERS_SA does not Granger Cause RLX_GERMANY_SA	189	0.11268	0.8935
RLX_GERMANY_SA does not Granger Cause RLX_OTHERS_SA		2.99458	0.0525

RLX_PORTUGAL_SA does not Granger Cause RLX_GERMANY_SA	189	0.39126	0.6768
RLX_GERMANY_SA does not Granger Cause RLX_PORTUGAL_SA		0.06207	0.9398
RLX_SPAIN_SA does not Granger Cause RLX_GERMANY_SA	189	5.98805	0.0030
RLX_GERMANY_SA does not Granger Cause RLX_SPAIN_SA		1.26325	0.2852
RLX_TOTAL_SA does not Granger Cause RLX_GERMANY_SA	189	1.08404	0.3404
RLX_GERMANY_SA does not Granger Cause RLX_TOTAL_SA		1.47549	0.2314
RLX_UK_SA does not Granger Cause RLX_GERMANY_SA	189	3.07208	0.0487
RLX_GERMANY_SA does not Granger Cause RLX_UK_SA		0.85468	0.4271
RLX_OTHERS_SA does not Granger Cause RLX_ITALY_SA	189	3.42679	0.0346
RLX_ITALY_SA does not Granger Cause RLX_OTHERS_SA		0.92516	0.3983
RLX_PORTUGAL_SA does not Granger Cause RLX_ITALY_SA	189	0.18578	0.8306
RLX_ITALY_SA does not Granger Cause RLX_PORTUGAL_SA		1.42208	0.2439
RLX_SPAIN_SA does not Granger Cause RLX_ITALY_SA	189	1.00417	0.3683
RLX_ITALY_SA does not Granger Cause RLX_SPAIN_SA		5.59167	0.0044
RLX_TOTAL_SA does not Granger Cause RLX_ITALY_SA	189	3.35136	0.0372
RLX_ITALY_SA does not Granger Cause RLX_TOTAL_SA		1.59725	0.2052
RLX_UK_SA does not Granger Cause RLX_ITALY_SA	189	2.60170	0.0769
RLX_ITALY_SA does not Granger Cause RLX_UK_SA		1.81181	0.1663
RLX_PORTUGAL_SA does not Granger Cause RLX_OTHERS_SA	189	0.18796	0.8288
RLX_OTHERS_SA does not Granger Cause RLX_PORTUGAL_SA		0.16373	0.8491
RLX_SPAIN_SA does not Granger Cause RLX_OTHERS_SA	189	0.07608	0.9268
RLX_OTHERS_SA does not Granger Cause RLX_SPAIN_SA		1.29341	0.2768
RLX_TOTAL_SA does not Granger Cause RLX_OTHERS_SA	189	0.07504	0.9277
RLX_OTHERS_SA does not Granger Cause RLX_TOTAL_SA		5.72805	0.0039
RLX_UK_SA does not Granger Cause RLX_OTHERS_SA	189	4.33214	0.0145
RLX_OTHERS_SA does not Granger Cause RLX_UK_SA		0.32898	0.7201
RLX_SPAIN_SA does not Granger Cause RLX_PORTUGAL_SA	189	0.65202	0.5222
RLX_PORTUGAL_SA does not Granger Cause RLX_SPAIN_SA		0.02449	0.9758
RLX_TOTAL_SA does not Granger Cause RLX_PORTUGAL_SA	189	0.04579	0.9553
RLX_PORTUGAL_SA does not Granger Cause RLX_TOTAL_SA		0.59164	0.5545
RLX_UK_SA does not Granger Cause RLX_PORTUGAL_SA	189	0.34516	0.7086
RLX_PORTUGAL_SA does not Granger Cause RLX_UK_SA		0.10419	0.9011
RLX_TOTAL_SA does not Granger Cause RLX_SPAIN_SA	189	2.09656	0.1258
RLX_SPAIN_SA does not Granger Cause RLX_TOTAL_SA		7.32979	0.0009
RLX_UK_SA does not Granger Cause RLX_SPAIN_SA	189	4.12131	0.0177
RLX_SPAIN_SA does not Granger Cause RLX_UK_SA		2.26107	0.1071
RLX_UK_SA does not Granger Cause RLX_TOTAL_SA	189	1.62302	0.2001
RLX_TOTAL_SA does not Granger Cause RLX_UK_SA		3.02671	0.0509

Pairwise Granger Causality Tests

Sample: 2001M01 2016M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ROP_FRANCE_SA does not Granger Cause ROP_BRAZIL_SA	189	1.46393	0.2340
ROP_BRAZIL_SA does not Granger Cause ROP_FRANCE_SA		0.02328	0.9770
ROP_GERMANY_SA does not Granger Cause ROP_BRAZIL_SA	189	1.35434	0.2607
ROP_BRAZIL_SA does not Granger Cause ROP_GERMANY_SA		1.67341	0.1904
ROP_ITALY_SA does not Granger Cause ROP_BRAZIL_SA	189	3.30635	0.0388
ROP_BRAZIL_SA does not Granger Cause ROP_ITALY_SA		2.26364	0.1069
ROP_OTHERS_SA does not Granger Cause ROP_BRAZIL_SA	189	1.11145	0.3313
ROP_BRAZIL_SA does not Granger Cause ROP_OTHERS_SA		1.97851	0.1412
ROP_PORTUGAL_SA does not Granger Cause ROP_BRAZIL_SA	189	0.76052	0.4689
ROP_BRAZIL_SA does not Granger Cause ROP_PORTUGAL_SA		0.66533	0.5153
ROP_SPAIN_SA does not Granger Cause ROP_BRAZIL_SA	189	0.18361	0.8324
ROP_BRAZIL_SA does not Granger Cause ROP_SPAIN_SA		0.71981	0.4882
ROP_TOTAL_SA does not Granger Cause ROP_BRAZIL_SA	189	0.20951	0.8112
ROP_BRAZIL_SA does not Granger Cause ROP_TOTAL_SA		2.72362	0.0683
ROP_UK_SA does not Granger Cause ROP_BRAZIL_SA	189	1.35256	0.2611
ROP_BRAZIL_SA does not Granger Cause ROP_UK_SA		0.24485	0.7831
ROP_GERMANY_SA does not Granger Cause ROP_FRANCE_SA	189	1.50284	0.2252
ROP_FRANCE_SA does not Granger Cause ROP_GERMANY_SA		0.26136	0.7703
ROP_ITALY_SA does not Granger Cause ROP_FRANCE_SA	189	0.13760	0.8715
ROP_FRANCE_SA does not Granger Cause ROP_ITALY_SA		1.13682	0.3231
ROP_OTHERS_SA does not Granger Cause ROP_FRANCE_SA	189	1.89032	0.1539
ROP_FRANCE_SA does not Granger Cause ROP_OTHERS_SA		2.18206	0.1157
ROP_PORTUGAL_SA does not Granger Cause ROP_FRANCE_SA	189	0.11283	0.8934
ROP_FRANCE_SA does not Granger Cause ROP_PORTUGAL_SA		1.28647	0.2787
ROP_SPAIN_SA does not Granger Cause ROP_FRANCE_SA	189	1.03633	0.3568
ROP_FRANCE_SA does not Granger Cause ROP_SPAIN_SA		0.42456	0.6547
ROP_TOTAL_SA does not Granger Cause ROP_FRANCE_SA	189	0.00933	0.9907
ROP_FRANCE_SA does not Granger Cause ROP_TOTAL_SA		0.38335	0.6821
ROP_UK_SA does not Granger Cause ROP_FRANCE_SA	189	0.94468	0.3907
ROP_FRANCE_SA does not Granger Cause ROP_UK_SA		1.48635	0.2289
ROP_ITALY_SA does not Granger Cause ROP_GERMANY_SA	189	0.97683	0.3784
ROP_GERMANY_SA does not Granger Cause ROP_ITALY_SA		0.40460	0.6678
ROP_OTHERS_SA does not Granger Cause ROP_GERMANY_SA	189	2.05607	0.1309
ROP_GERMANY_SA does not Granger Cause ROP_OTHERS_SA		2.65580	0.0729

ROP_PORTUGAL_SA does not Granger Cause ROP_GERMANY_SA	189	1.12000	0.3285
ROP_GERMANY_SA does not Granger Cause ROP_PORTUGAL_SA		0.64381	0.5265
ROP_SPAIN_SA does not Granger Cause ROP_GERMANY_SA	189	0.26018	0.7712
ROP_GERMANY_SA does not Granger Cause ROP_SPAIN_SA		0.78261	0.4587
ROP_TOTAL_SA does not Granger Cause ROP_GERMANY_SA	189	5.28542	0.0059
ROP_GERMANY_SA does not Granger Cause ROP_TOTAL_SA		1.17253	0.3119
ROP_UK_SA does not Granger Cause ROP_GERMANY_SA	189	3.45156	0.0338
ROP_GERMANY_SA does not Granger Cause ROP_UK_SA		0.33859	0.7132
ROP_OTHERS_SA does not Granger Cause ROP_ITALY_SA	189	2.05795	0.1306
ROP_ITALY_SA does not Granger Cause ROP_OTHERS_SA		0.76819	0.4653
ROP_PORTUGAL_SA does not Granger Cause ROP_ITALY_SA	189	0.23193	0.7932
ROP_ITALY_SA does not Granger Cause ROP_PORTUGAL_SA		0.33528	0.7156
ROP_SPAIN_SA does not Granger Cause ROP_ITALY_SA	189	0.84841	0.4298
ROP_ITALY_SA does not Granger Cause ROP_SPAIN_SA		3.21440	0.0424
ROP_TOTAL_SA does not Granger Cause ROP_ITALY_SA	189	0.45966	0.6322
ROP_ITALY_SA does not Granger Cause ROP_TOTAL_SA		3.51016	0.0319
ROP_UK_SA does not Granger Cause ROP_ITALY_SA	189	0.42815	0.6524
ROP_ITALY_SA does not Granger Cause ROP_UK_SA		0.78599	0.4572
ROP_PORTUGAL_SA does not Granger Cause ROP_OTHERS_SA	189	0.57839	0.5618
ROP_OTHERS_SA does not Granger Cause ROP_PORTUGAL_SA		0.27745	0.7580
ROP_SPAIN_SA does not Granger Cause ROP_OTHERS_SA	189	0.98197	0.3765
ROP_OTHERS_SA does not Granger Cause ROP_SPAIN_SA		3.55144	0.0307
ROP_TOTAL_SA does not Granger Cause ROP_OTHERS_SA	189	0.67991	0.5079
ROP_OTHERS_SA does not Granger Cause ROP_TOTAL_SA		1.45100	0.2370
ROP_UK_SA does not Granger Cause ROP_OTHERS_SA	189	7.32662	0.0009
ROP_OTHERS_SA does not Granger Cause ROP_UK_SA		1.32147	0.2693
ROP_SPAIN_SA does not Granger Cause ROP_PORTUGAL_SA	189	3.31493	0.0385
ROP_PORTUGAL_SA does not Granger Cause ROP_SPAIN_SA		0.67940	0.5082
ROP_TOTAL_SA does not Granger Cause ROP_PORTUGAL_SA	189	3.83073	0.0234
ROP_PORTUGAL_SA does not Granger Cause ROP_TOTAL_SA		0.10889	0.8969
ROP_UK_SA does not Granger Cause ROP_PORTUGAL_SA	189	0.62678	0.5354
ROP_PORTUGAL_SA does not Granger Cause ROP_UK_SA		0.00683	0.9932
ROP_TOTAL_SA does not Granger Cause ROP_SPAIN_SA	189	0.74044	0.4783
ROP_SPAIN_SA does not Granger Cause ROP_TOTAL_SA		1.96167	0.1436
ROP_UK_SA does not Granger Cause ROP_SPAIN_SA	189	0.05347	0.9479
ROP_SPAIN_SA does not Granger Cause ROP_UK_SA		0.15735	0.8545
ROP_UK_SA does not Granger Cause ROP_TOTAL_SA	189	2.33048	0.1001
ROP_TOTAL_SA does not Granger Cause ROP_UK_SA		0.98151	0.3767

Appendix E - EViews outputs for ARDL models in Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ARDL
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_BRAZIL_SA(-1)	-0.467322	0.073221	-6.382388	0.0000
RCB_BRAZIL_SA(-2)	-0.280645	0.077996	-3.598179	0.0004
RCB_BRAZIL_SA(-3)	-0.116888	0.073043	-1.600256	0.1113
C	0.018572	0.015875	1.169947	0.2435

R-squared	0.185546	Mean dependent var	0.009926
Adjusted R-squared	0.172266	S.D. dependent var	0.237875
S.E. of regression	0.216418	Akaike info criterion	-0.202159
Sum squared resid	8.617998	Schwarz criterion	-0.133298
Log likelihood	23.00294	Hannan-Quinn criter.	-0.174259
F-statistic	13.97270	Durbin-Watson stat	2.020851
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_FRANCE_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_FRANCE_SA(-1)	-0.783850	0.073408	-10.67794	0.0000
RCB_FRANCE_SA(-2)	-0.559829	0.089840	-6.231375	0.0000
RCB_FRANCE_SA(-3)	-0.363350	0.089847	-4.044098	0.0001
RCB_FRANCE_SA(-4)	-0.137507	0.073497	-1.870912	0.0630
C	0.007004	0.013473	0.519894	0.6038

R-squared	0.387418	Mean dependent var	0.002687
Adjusted R-squared	0.373954	S.D. dependent var	0.232561
S.E. of regression	0.184010	Akaike info criterion	-0.521284
Sum squared resid	6.162432	Schwarz criterion	-0.434891
Log likelihood	53.74006	Hannan-Quinn criter.	-0.486277
F-statistic	28.77575	Durbin-Watson stat	2.008004
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_GERMANY_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_GERMANY_SA(-1)	-0.639569	0.073099	-8.749395	0.0000
RCB_GERMANY_SA(-2)	-0.494175	0.084340	-5.859334	0.0000
RCB_GERMANY_SA(-3)	-0.301664	0.083875	-3.596588	0.0004
RCB_GERMANY_SA(-4)	-0.129760	0.072784	-1.782807	0.0763
C	0.004226	0.014443	0.292635	0.7701

R-squared	0.303019	Mean dependent var	0.002013
Adjusted R-squared	0.287701	S.D. dependent var	0.233975
S.E. of regression	0.197470	Akaike info criterion	-0.380087
Sum squared resid	7.096976	Schwarz criterion	-0.293694
Log likelihood	40.53812	Hannan-Quinn criter.	-0.345080
F-statistic	19.78157	Durbin-Watson stat	2.027013
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_ITALY_SA
Method: ARDL
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Maximum dependent lags: 7 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (7 lags, automatic):
Fixed regressors: C
Number of models evalulated: 7
Selected Model: ARDL(6)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_ITALY_SA(-1)	-0.750783	0.074288	-10.10634	0.0000
RCB_ITALY_SA(-2)	-0.537556	0.092043	-5.840255	0.0000
RCB_ITALY_SA(-3)	-0.384194	0.098332	-3.907096	0.0001
RCB_ITALY_SA(-4)	-0.272645	0.098214	-2.776022	0.0061
RCB_ITALY_SA(-5)	-0.187328	0.091758	-2.041549	0.0427
RCB_ITALY_SA(-6)	-0.128402	0.074053	-1.733933	0.0847
C	-0.001031	0.014878	-0.069318	0.9448

R-squared	0.366319	Mean dependent var	6.83E-05
Adjusted R-squared	0.344959	S.D. dependent var	0.250023
S.E. of regression	0.202355	Akaike info criterion	-0.320483
Sum squared resid	7.288664	Schwarz criterion	-0.198631
Log likelihood	36.64465	Hannan-Quinn criter.	-0.271099
F-statistic	17.14973	Durbin-Watson stat	2.000517
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_OTHERS_SA
Method: ARDL
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Maximum dependent lags: 7 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (7 lags, automatic):
Fixed regressors: C
Number of models evalulated: 7
Selected Model: ARDL(6)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_OTHERS_SA(-1)	-0.508432	0.073674	-6.901066	0.0000
RCB_OTHERS_SA(-2)	-0.455478	0.080565	-5.653534	0.0000
RCB_OTHERS_SA(-3)	-0.326439	0.085621	-3.812594	0.0002
RCB_OTHERS_SA(-4)	-0.239572	0.085652	-2.797048	0.0057
RCB_OTHERS_SA(-5)	-0.267767	0.080422	-3.329538	0.0011
RCB_OTHERS_SA(-6)	-0.181644	0.073604	-2.467867	0.0145
C	0.012951	0.010692	1.211224	0.2274

R-squared	0.253435	Mean dependent var	0.004557
Adjusted R-squared	0.228270	S.D. dependent var	0.163992
S.E. of regression	0.144064	Akaike info criterion	-1.000014
Sum squared resid	3.694293	Schwarz criterion	-0.878163
Log likelihood	99.50130	Hannan-Quinn criter.	-0.950631
F-statistic	10.07087	Durbin-Watson stat	2.021344
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_PORTUGAL_SA
Method: ARDL
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Maximum dependent lags: 7 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (7 lags, automatic):
Fixed regressors: C
Number of models evalulated: 7
Selected Model: ARDL(6)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_PORTUGAL_SA(-1)	-0.485371	0.074143	-6.546406	0.0000
RCB_PORTUGAL_SA(-2)	-0.299232	0.082858	-3.611391	0.0004
RCB_PORTUGAL_SA(-3)	-0.181430	0.083110	-2.183013	0.0303
RCB_PORTUGAL_SA(-4)	-0.291758	0.083165	-3.508204	0.0006
RCB_PORTUGAL_SA(-5)	0.019603	0.082843	0.236632	0.8132
RCB_PORTUGAL_SA(-6)	0.149434	0.074296	2.011322	0.0458
C	0.005081	0.006201	0.819428	0.4136

R-squared	0.284294	Mean dependent var	0.002621
Adjusted R-squared	0.260169	S.D. dependent var	0.097487
S.E. of regression	0.083852	Akaike info criterion	-2.082434
Sum squared resid	1.251532	Schwarz criterion	-1.960583
Log likelihood	199.6252	Hannan-Quinn criter.	-2.033051
F-statistic	11.78426	Durbin-Watson stat	1.970844
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_SPAIN_SA
Method: ARDL
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Maximum dependent lags: 8 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic):
Fixed regressors: C
Number of models evalulated: 8
Selected Model: ARDL(7)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_SPAIN_SA(-1)	-1.079913	0.074807	-14.43608	0.0000
RCB_SPAIN_SA(-2)	-0.974368	0.109407	-8.905921	0.0000
RCB_SPAIN_SA(-3)	-0.738367	0.128429	-5.749211	0.0000
RCB_SPAIN_SA(-4)	-0.550073	0.134442	-4.091531	0.0001
RCB_SPAIN_SA(-5)	-0.442296	0.129431	-3.417231	0.0008
RCB_SPAIN_SA(-6)	-0.323293	0.110554	-2.924307	0.0039
RCB_SPAIN_SA(-7)	-0.155346	0.076000	-2.044029	0.0424
C	0.011447	0.017888	0.639933	0.5230

R-squared	0.552796	Mean dependent var	0.001825
Adjusted R-squared	0.535010	S.D. dependent var	0.354168
S.E. of regression	0.241508	Akaike info criterion	0.038677
Sum squared resid	10.26540	Schwarz criterion	0.178457
Log likelihood	4.441740	Hannan-Quinn criter.	0.095331
F-statistic	31.07954	Durbin-Watson stat	1.990636
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_TOTAL_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_TOTAL_SA(-1)	-0.489958	0.073005	-6.711328	0.0000
RCB_TOTAL_SA(-2)	-0.451447	0.080982	-5.574631	0.0000
RCB_TOTAL_SA(-3)	-0.127024	0.081044	-1.567349	0.1188
RCB_TOTAL_SA(-4)	-0.173500	0.073056	-2.374871	0.0186
C	0.006891	0.005548	1.242160	0.2158

R-squared	0.258687	Mean dependent var	0.003076
Adjusted R-squared	0.242394	S.D. dependent var	0.086508
S.E. of regression	0.075297	Akaike info criterion	-2.308376
Sum squared resid	1.031877	Schwarz criterion	-2.221983
Log likelihood	220.8332	Hannan-Quinn criter.	-2.273370
F-statistic	15.87755	Durbin-Watson stat	2.014090
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RCB_UK_SA
Method: ARDL
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Maximum dependent lags: 7 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (7 lags, automatic):
Fixed regressors: C
Number of models evalulated: 7
Selected Model: ARDL(6)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RCB_UK_SA(-1)	-0.617080	0.074015	-8.337192	0.0000
RCB_UK_SA(-2)	-0.305050	0.085829	-3.554158	0.0005
RCB_UK_SA(-3)	-0.370872	0.086831	-4.271206	0.0000
RCB_UK_SA(-4)	-0.237064	0.086723	-2.733583	0.0069
RCB_UK_SA(-5)	-0.191710	0.085476	-2.242842	0.0261
RCB_UK_SA(-6)	-0.160034	0.073043	-2.190943	0.0298
C	0.004815	0.016363	0.294243	0.7689

R-squared	0.320143	Mean dependent var	0.001506
Adjusted R-squared	0.297226	S.D. dependent var	0.265361
S.E. of regression	0.222457	Akaike info criterion	-0.131067
Sum squared resid	8.808669	Schwarz criterion	-0.009215
Log likelihood	19.12367	Hannan-Quinn criter.	-0.081683
F-statistic	13.96993	Durbin-Watson stat	2.004425
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_FRANCE_SA
Method: ARDL
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_FRANCE_SA(-1)	-0.561412	0.071453	-7.857092	0.0000
RLX_FRANCE_SA(-2)	-0.203137	0.066820	-3.040050	0.0027
C	0.013628	0.005755	2.368010	0.0189

R-squared	0.250712	Mean dependent var	0.007824
Adjusted R-squared	0.242655	S.D. dependent var	0.089919
S.E. of regression	0.078252	Akaike info criterion	-2.242009
Sum squared resid	1.138959	Schwarz criterion	-2.190553
Log likelihood	214.8699	Hannan-Quinn criter.	-2.221163
F-statistic	31.11784	Durbin-Watson stat	2.013770
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_BRAZIL_SA
Method: ARDL
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_BRAZIL_SA(-1)	-0.422657	0.071112	-5.943584	0.0000
RLX_BRAZIL_SA(-2)	-0.244226	0.072273	-3.379206	0.0009
C	0.013397	0.009381	1.428119	0.1549

R-squared	0.167969	Mean dependent var	0.007812
Adjusted R-squared	0.159023	S.D. dependent var	0.139894
S.E. of regression	0.128289	Akaike info criterion	-1.253310
Sum squared resid	3.061222	Schwarz criterion	-1.201853
Log likelihood	121.4378	Hannan-Quinn criter.	-1.232463
F-statistic	18.77472	Durbin-Watson stat	2.031061
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_GERMANY_SA
Method: ARDL
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(5)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_GERMANY_SA(-1)	-0.503042	0.074039	-6.794289	0.0000
RLX_GERMANY_SA(-2)	-0.368703	0.080697	-4.568966	0.0000
RLX_GERMANY_SA(-3)	-0.241540	0.083130	-2.905565	0.0041
RLX_GERMANY_SA(-4)	-0.201450	0.080649	-2.497873	0.0134
RLX_GERMANY_SA(-5)	-0.114172	0.072678	-1.570936	0.1180
C	0.010526	0.006532	1.611502	0.1088

R-squared	0.217117	Mean dependent var	0.004464
Adjusted R-squared	0.195370	S.D. dependent var	0.097891
S.E. of regression	0.087810	Akaike info criterion	-1.995562
Sum squared resid	1.387900	Schwarz criterion	-1.891505
Log likelihood	191.5872	Hannan-Quinn criter.	-1.953394
F-statistic	9.983863	Durbin-Watson stat	1.990768
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_ITALY_SA
Method: ARDL
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_ITALY_SA(-1)	-0.542795	0.068639	-7.907986	0.0000
RLX_ITALY_SA(-2)	-0.353019	0.068602	-5.145867	0.0000
C	0.005265	0.007469	0.704955	0.4817

R-squared	0.265334	Mean dependent var	0.002869
Adjusted R-squared	0.257434	S.D. dependent var	0.119055
S.E. of regression	0.102592	Akaike info criterion	-1.700366
Sum squared resid	1.957675	Schwarz criterion	-1.648910
Log likelihood	163.6846	Hannan-Quinn criter.	-1.679520
F-statistic	33.58810	Durbin-Watson stat	2.028456
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_OTHERS_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_OTHERS_SA(-1)	-0.431578	0.073511	-5.870932	0.0000
RLX_OTHERS_SA(-2)	-0.383192	0.078804	-4.862601	0.0000
RLX_OTHERS_SA(-3)	-0.149117	0.079106	-1.885017	0.0610
RLX_OTHERS_SA(-4)	-0.115303	0.072625	-1.587661	0.1141
C	0.012612	0.004338	2.907504	0.0041

R-squared	0.195495	Mean dependent var	0.006438
Adjusted R-squared	0.177814	S.D. dependent var	0.062842
S.E. of regression	0.056981	Akaike info criterion	-2.865814
Sum squared resid	0.590930	Schwarz criterion	-2.779421
Log likelihood	272.9536	Hannan-Quinn criter.	-2.830807
F-statistic	11.05653	Durbin-Watson stat	2.010111
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_PORTUGAL_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_PORTUGAL_SA(-1)	-0.471967	0.073775	-6.397401	0.0000
RLX_PORTUGAL_SA(-2)	-0.271026	0.080351	-3.373042	0.0009
RLX_PORTUGAL_SA(-3)	-0.180796	0.080351	-2.250081	0.0256
RLX_PORTUGAL_SA(-4)	-0.106368	0.074143	-1.434644	0.1531
C	0.004795	0.003203	1.496805	0.1362

R-squared	0.187024	Mean dependent var	0.002444
Adjusted R-squared	0.169157	S.D. dependent var	0.047538
S.E. of regression	0.043331	Akaike info criterion	-3.413527
Sum squared resid	0.341717	Schwarz criterion	-3.327134
Log likelihood	324.1648	Hannan-Quinn criter.	-3.378520
F-statistic	10.46724	Durbin-Watson stat	1.998843
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_SPAIN_SA
Method: ARDL
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(5)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_SPAIN_SA(-1)	-1.078674	0.074114	-14.55420	0.0000
RLX_SPAIN_SA(-2)	-0.830968	0.107973	-7.696097	0.0000
RLX_SPAIN_SA(-3)	-0.539515	0.117489	-4.592060	0.0000
RLX_SPAIN_SA(-4)	-0.223694	0.107545	-2.080015	0.0389
RLX_SPAIN_SA(-5)	-0.105979	0.073837	-1.435316	0.1529
C	0.007782	0.012394	0.627906	0.5309

R-squared	0.570433	Mean dependent var	0.001713
Adjusted R-squared	0.558500	S.D. dependent var	0.253937
S.E. of regression	0.168730	Akaike info criterion	-0.689309
Sum squared resid	5.124558	Schwarz criterion	-0.585253
Log likelihood	70.10575	Hannan-Quinn criter.	-0.647142
F-statistic	47.80530	Durbin-Watson stat	2.002197
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_TOTAL_SA
Method: ARDL
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_TOTAL_SA(-1)	-0.622638	0.073347	-8.488953	0.0000
RLX_TOTAL_SA(-2)	-0.373145	0.082440	-4.526265	0.0000
RLX_TOTAL_SA(-3)	-0.100387	0.073692	-1.362250	0.1748
C	0.009370	0.003534	2.651439	0.0087

R-squared	0.288313	Mean dependent var	0.004629
Adjusted R-squared	0.276709	S.D. dependent var	0.055562
S.E. of regression	0.047254	Akaike info criterion	-3.245515
Sum squared resid	0.410860	Schwarz criterion	-3.176654
Log likelihood	309.0784	Hannan-Quinn criter.	-3.217615
F-statistic	24.84685	Durbin-Watson stat	1.973798
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RLX_UK_SA
Method: ARDL
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RLX_UK_SA(-1)	-0.279016	0.072153	-3.867012	0.0002
RLX_UK_SA(-2)	-0.186913	0.074574	-2.506408	0.0131
RLX_UK_SA(-3)	-0.181732	0.072668	-2.500844	0.0133
C	0.006188	0.006220	0.994842	0.3211

R-squared	0.099272	Mean dependent var	0.004140
Adjusted R-squared	0.084587	S.D. dependent var	0.088888
S.E. of regression	0.085045	Akaike info criterion	-2.070216
Sum squared resid	1.330820	Schwarz criterion	-2.001356
Log likelihood	198.6003	Hannan-Quinn criter.	-2.042317
F-statistic	6.759771	Durbin-Watson stat	1.998237
Prob(F-statistic)	0.000238		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_BRAZIL_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_BRAZIL_SA(-1)	-0.584909	0.073561	-7.951323	0.0000
ROP_BRAZIL_SA(-2)	-0.404970	0.084457	-4.794986	0.0000
ROP_BRAZIL_SA(-3)	-0.226811	0.085042	-2.667047	0.0083
ROP_BRAZIL_SA(-4)	-0.116818	0.074563	-1.566690	0.1189
C	0.025084	0.012405	2.022020	0.0446

R-squared	0.261231	Mean dependent var	0.010998
Adjusted R-squared	0.244994	S.D. dependent var	0.191630
S.E. of regression	0.166510	Akaike info criterion	-0.721152
Sum squared resid	5.046037	Schwarz criterion	-0.634759
Log likelihood	72.42775	Hannan-Quinn criter.	-0.686146
F-statistic	16.08891	Durbin-Watson stat	1.994862
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_FRANCE_SA
Method: ARDL
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(5)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_FRANCE_SA(-1)	-0.468142	0.073515	-6.368021	0.0000
ROP_FRANCE_SA(-2)	-0.182428	0.080343	-2.270619	0.0244
ROP_FRANCE_SA(-3)	-0.082331	0.080584	-1.021677	0.3083
ROP_FRANCE_SA(-4)	-0.155653	0.078028	-1.994828	0.0476
ROP_FRANCE_SA(-5)	-0.139833	0.071734	-1.949317	0.0528
C	0.021081	0.008195	2.572465	0.0109

R-squared	0.196539	Mean dependent var	0.010475
Adjusted R-squared	0.174221	S.D. dependent var	0.117403
S.E. of regression	0.106687	Akaike info criterion	-1.606102
Sum squared resid	2.048795	Schwarz criterion	-1.502045
Log likelihood	155.3675	Hannan-Quinn criter.	-1.563934
F-statistic	8.806157	Durbin-Watson stat	1.978551
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_GERMANY_SA
Method: ARDL
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Maximum dependent lags: 8 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic):
Fixed regressors: C
Number of models evalulated: 8
Selected Model: ARDL(7)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_GERMANY_SA(-1)	-0.686481	0.073977	-9.279634	0.0000
ROP_GERMANY_SA(-2)	-0.398650	0.088792	-4.489710	0.0000
ROP_GERMANY_SA(-3)	-0.273224	0.092481	-2.954360	0.0036
ROP_GERMANY_SA(-4)	-0.317235	0.092125	-3.443539	0.0007
ROP_GERMANY_SA(-5)	-0.179105	0.092870	-1.928563	0.0554
ROP_GERMANY_SA(-6)	0.000580	0.088041	0.006587	0.9948
ROP_GERMANY_SA(-7)	0.190939	0.071537	2.669105	0.0083
C	0.016341	0.010582	1.544131	0.1244

R-squared	0.382703	Mean dependent var	0.006919
Adjusted R-squared	0.358151	S.D. dependent var	0.172735
S.E. of regression	0.138387	Akaike info criterion	-1.075018
Sum squared resid	3.370578	Schwarz criterion	-0.935238
Log likelihood	106.9016	Hannan-Quinn criter.	-1.018363
F-statistic	15.58770	Durbin-Watson stat	1.962451
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_OTHERS_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_OTHERS_SA(-1)	-0.559789	0.073441	-7.622243	0.0000
ROP_OTHERS_SA(-2)	-0.347991	0.083948	-4.145299	0.0001
ROP_OTHERS_SA(-3)	-0.184984	0.084112	-2.199251	0.0291
ROP_OTHERS_SA(-4)	-0.127878	0.073916	-1.730036	0.0853
C	0.018617	0.007853	2.370727	0.0188

R-squared	0.245483	Mean dependent var	0.009085
Adjusted R-squared	0.228900	S.D. dependent var	0.119260
S.E. of regression	0.104725	Akaike info criterion	-1.648584
Sum squared resid	1.996053	Schwarz criterion	-1.562190
Log likelihood	159.1426	Hannan-Quinn criter.	-1.613577
F-statistic	14.80348	Durbin-Watson stat	2.024728
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_ITALY_SA
Method: ARDL
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Maximum dependent lags: 7 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (7 lags, automatic):
Fixed regressors: C
Number of models evalulated: 7
Selected Model: ARDL(6)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_ITALY_SA(-1)	-0.328103	0.073621	-4.456659	0.0000
ROP_ITALY_SA(-2)	-0.269143	0.077475	-3.473919	0.0006
ROP_ITALY_SA(-3)	-0.233827	0.078639	-2.973427	0.0034
ROP_ITALY_SA(-4)	-0.225970	0.078260	-2.887437	0.0044
ROP_ITALY_SA(-5)	-0.110758	0.077243	-1.433898	0.1534
ROP_ITALY_SA(-6)	-0.190377	0.073641	-2.585203	0.0105
C	0.011688	0.009511	1.228809	0.2208

R-squared	0.151656	Mean dependent var	0.005629
Adjusted R-squared	0.123060	S.D. dependent var	0.137086
S.E. of regression	0.128374	Akaike info criterion	-1.230630
Sum squared resid	2.933433	Schwarz criterion	-1.108778
Log likelihood	120.8332	Hannan-Quinn criter.	-1.181246
F-statistic	5.303410	Durbin-Watson stat	2.009473
Prob(F-statistic)	0.000047		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_PORTUGAL_SA
Method: ARDL
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_PORTUGAL_SA(-1)	-0.612367	0.073528	-8.328361	0.0000
ROP_PORTUGAL_SA(-2)	-0.362744	0.085644	-4.235469	0.0000
ROP_PORTUGAL_SA(-3)	-0.178225	0.085415	-2.086576	0.0383
ROP_PORTUGAL_SA(-4)	-0.126543	0.073654	-1.718071	0.0875
C	0.005407	0.004591	1.177703	0.2405

R-squared	0.279682	Mean dependent var	0.002375
Adjusted R-squared	0.263851	S.D. dependent var	0.072657
S.E. of regression	0.062339	Akaike info criterion	-2.686073
Sum squared resid	0.707288	Schwarz criterion	-2.599680
Log likelihood	256.1478	Hannan-Quinn criter.	-2.651067
F-statistic	17.66656	Durbin-Watson stat	2.013879
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_SPAIN_SA
Method: ARDL
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(5)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_SPAIN_SA(-1)	-1.064595	0.073912	-14.40351	0.0000
ROP_SPAIN_SA(-2)	-0.873359	0.105655	-8.266146	0.0000
ROP_SPAIN_SA(-3)	-0.598235	0.115683	-5.171332	0.0000
ROP_SPAIN_SA(-4)	-0.304301	0.105568	-2.882500	0.0044
ROP_SPAIN_SA(-5)	-0.126490	0.073703	-1.716218	0.0878
C	0.027810	0.013961	1.991908	0.0479

R-squared	0.549194	Mean dependent var	0.007587
Adjusted R-squared	0.536672	S.D. dependent var	0.274898
S.E. of regression	0.187118	Akaike info criterion	-0.482427
Sum squared resid	6.302374	Schwarz criterion	-0.378371
Log likelihood	50.86573	Hannan-Quinn criter.	-0.440260
F-statistic	43.85697	Durbin-Watson stat	2.023725
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_TOTAL_SA
Method: ARDL
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_TOTAL_SA(-1)	-0.548907	0.072031	-7.620466	0.0000
ROP_TOTAL_SA(-2)	-0.185509	0.071926	-2.579149	0.0107
C	0.010445	0.004034	2.589579	0.0104

R-squared	0.241911	Mean dependent var	0.005956
Adjusted R-squared	0.233760	S.D. dependent var	0.062289
S.E. of regression	0.054525	Akaike info criterion	-2.964578
Sum squared resid	0.552969	Schwarz criterion	-2.913121
Log likelihood	283.1526	Hannan-Quinn criter.	-2.943732
F-statistic	29.67694	Durbin-Watson stat	2.023740
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: ROP_UK_SA
Method: ARDL
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Maximum dependent lags: 6 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (6 lags, automatic):
Fixed regressors: C
Number of models evalulated: 6
Selected Model: ARDL(5)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROP_UK_SA(-1)	-0.688031	0.074222	-9.269950	0.0000
ROP_UK_SA(-2)	-0.408731	0.089163	-4.584061	0.0000
ROP_UK_SA(-3)	-0.362731	0.091006	-3.985816	0.0001
ROP_UK_SA(-4)	-0.256916	0.089264	-2.878156	0.0045
ROP_UK_SA(-5)	-0.152434	0.073510	-2.073660	0.0395
C	0.017819	0.013289	1.340881	0.1816

R-squared	0.335504	Mean dependent var	0.007130
Adjusted R-squared	0.317046	S.D. dependent var	0.217634
S.E. of regression	0.179855	Akaike info criterion	-0.561604
Sum squared resid	5.822616	Schwarz criterion	-0.457548
Log likelihood	58.22916	Hannan-Quinn criter.	-0.519436
F-statistic	18.17643	Durbin-Watson stat	1.987456
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix F - EViews outputs for ARCH/GARCH models without lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.019221	0.013227	1.453111	0.1462
	Variance Equation			
C	0.012033	0.004381	2.746638	0.0060
RESID(-1)^2	0.395530	0.135026	2.929296	0.0034
GARCH(-1)	0.417252	0.122250	3.413112	0.0006

R-squared	-0.001328	Mean dependent var	0.010582
Adjusted R-squared	-0.001328	S.D. dependent var	0.237659
S.E. of regression	0.237817	Akaike info criterion	-0.166064
Sum squared resid	10.74578	Schwarz criterion	-0.097954
Log likelihood	19.85911	Hannan-Quinn criter.	-0.138476
Durbin-Watson stat	2.715756		

Dependent Variable: RCB_FRANCE_SA
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010241	0.012386	0.826790	0.4084
	Variance Equation			
C	0.028366	0.003495	8.116147	0.0000
RESID(-1)^2	0.475126	0.145997	3.254355	0.0011

R-squared	-0.001022	Mean dependent var	0.002887
Adjusted R-squared	-0.001022	S.D. dependent var	0.230641
S.E. of regression	0.230759	Akaike info criterion	-0.243428
Sum squared resid	10.11747	Schwarz criterion	-0.192345
Log likelihood	26.24739	Hannan-Quinn criter.	-0.222737
Durbin-Watson stat	2.998048		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005708	0.014765	-0.386603	0.6991
	Variance Equation			
C	0.036885	0.003113	11.84756	0.0000
RESID(-1)^2	0.309357	0.116324	2.659443	0.0078

R-squared	-0.000421	Mean dependent var	-0.000923
Adjusted R-squared	-0.000421	S.D. dependent var	0.233956
S.E. of regression	0.234005	Akaike info criterion	-0.154953
Sum squared resid	10.40411	Schwarz criterion	-0.103870
Log likelihood	17.79801	Hannan-Quinn criter.	-0.134262
Durbin-Watson stat	2.800991		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005560	0.014476	-0.384117	0.7009
	Variance Equation			
C	0.044303	0.004005	11.06309	0.0000
RESID(-1)^2	0.245927	0.115202	2.134740	0.0328

R-squared	-0.000526	Mean dependent var	0.000119
Adjusted R-squared	-0.000526	S.D. dependent var	0.248254
S.E. of regression	0.248320	Akaike info criterion	-0.021872
Sum squared resid	11.71589	Schwarz criterion	0.029211
Log likelihood	5.088778	Hannan-Quinn criter.	-0.001181
Durbin-Watson stat	2.978866		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008290	0.009487	0.873776	0.3822
	Variance Equation			
C	0.018196	0.002311	7.874697	0.0000
RESID(-1)^2	0.322088	0.135578	2.375668	0.0175

R-squared	-0.000661	Mean dependent var	0.004136
Adjusted R-squared	-0.000661	S.D. dependent var	0.162017
S.E. of regression	0.162071	Akaike info criterion	-0.843813
Sum squared resid	4.990727	Schwarz criterion	-0.792730
Log likelihood	83.58417	Hannan-Quinn criter.	-0.823122
Durbin-Watson stat	2.605910		

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002703	0.004918	0.549518	0.5826
	Variance Equation			
C	0.002893	0.000744	3.888917	0.0001
RESID(-1)^2	0.590874	0.177476	3.329325	0.0009
GARCH(-1)	0.179585	0.089278	2.011522	0.0443

R-squared	-0.000012	Mean dependent var	0.002364
Adjusted R-squared	-0.000012	S.D. dependent var	0.096354
S.E. of regression	0.096354	Akaike info criterion	-1.993952
Sum squared resid	1.763987	Schwarz criterion	-1.925841
Log likelihood	194.4224	Hannan-Quinn criter.	-1.966364
Durbin-Watson stat	2.730037		

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.004067	0.015536	-0.261786	0.7935
	Variance Equation			
C	0.032460	0.003569	9.094953	0.0000
RESID(-1)^2	0.889812	0.161033	5.525648	0.0000

R-squared	-0.000246	Mean dependent var	0.001382
Adjusted R-squared	-0.000246	S.D. dependent var	0.348492
S.E. of regression	0.348535	Akaike info criterion	0.126514
Sum squared resid	23.08056	Schwarz criterion	0.177597
Log likelihood	-9.082099	Hannan-Quinn criter.	0.147205
Durbin-Watson stat	3.143137		

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000155	0.005034	-0.030845	0.9754
	Variance Equation			
C	0.004521	0.000527	8.574790	0.0000
RESID(-1)^2	0.377376	0.104664	3.605607	0.0003

R-squared	-0.001404	Mean dependent var	0.003045
Adjusted R-squared	-0.001404	S.D. dependent var	0.085637
S.E. of regression	0.085697	Akaike info criterion	-2.184758
Sum squared resid	1.395343	Schwarz criterion	-2.133675
Log likelihood	211.6444	Hannan-Quinn criter.	-2.164067
Durbin-Watson stat	2.680803		

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005610	0.014307	0.392132	0.6950
	Variance Equation			
C	0.043978	0.005208	8.443631	0.0000
RESID(-1)^2	0.345313	0.121185	2.849466	0.0044

R-squared	-0.000089	Mean dependent var	0.003128
Adjusted R-squared	-0.000089	S.D. dependent var	0.264508
S.E. of regression	0.264520	Akaike info criterion	0.068548
Sum squared resid	13.29441	Schwarz criterion	0.119631
Log likelihood	-3.546308	Hannan-Quinn criter.	0.089239
Durbin-Watson stat	2.931308		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009971	0.008333	1.196591	0.2315
	Variance Equation			
C	0.010722	0.000976	10.98479	0.0000
RESID(-1)^2	0.458650	0.136773	3.353361	0.0008

R-squared	-0.000096	Mean dependent var	0.008606
Adjusted R-squared	-0.000096	S.D. dependent var	0.139406
S.E. of regression	0.139413	Akaike info criterion	-1.305339
Sum squared resid	3.692826	Schwarz criterion	-1.254256
Log likelihood	127.6599	Hannan-Quinn criter.	-1.284648
Durbin-Watson stat	2.667082		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011986	0.005775	2.075357	0.0380
	Variance Equation			
C	0.005262	0.000400	13.15139	0.0000
RESID(-1)^2	0.369535	0.102424	3.607910	0.0003

R-squared	-0.003804	Mean dependent var	0.006056
Adjusted R-squared	-0.003804	S.D. dependent var	0.096401
S.E. of regression	0.096584	Akaike info criterion	-2.036416
Sum squared resid	1.772401	Schwarz criterion	-1.985334
Log likelihood	197.4778	Hannan-Quinn criter.	-2.015726
Durbin-Watson stat	2.732146		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004368	0.006168	0.708152	0.4789
	Variance Equation			
C	0.002208	0.001065	2.073790	0.0381
RESID(-1)^2	0.246186	0.105956	2.323462	0.0202
GARCH(-1)	0.526426	0.161019	3.269329	0.0011

R-squared	-0.000000	Mean dependent var	0.004335
Adjusted R-squared	-0.000000	S.D. dependent var	0.098782
S.E. of regression	0.098782	Akaike info criterion	-1.846276
Sum squared resid	1.854014	Schwarz criterion	-1.778166
Log likelihood	180.3194	Hannan-Quinn criter.	-1.818688
Durbin-Watson stat	2.702386		

Dependent Variable: RLX_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005864	0.006749	0.868858	0.3849
	Variance Equation			
C	0.009294	0.001446	6.427695	0.0000
RESID(-1)^2	0.368290	0.125478	2.935103	0.0033

R-squared	-0.000542	Mean dependent var	0.003112
Adjusted R-squared	-0.000542	S.D. dependent var	0.118493
S.E. of regression	0.118525	Akaike info criterion	-1.480308
Sum squared resid	2.669140	Schwarz criterion	-1.429225
Log likelihood	144.3694	Hannan-Quinn criter.	-1.459617
Durbin-Watson stat	2.797552		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005060	0.003779	1.338899	0.1806
	Variance Equation			
C	0.002075	0.000267	7.771712	0.0000
RESID(-1)^2	0.472414	0.140024	3.373803	0.0007

R-squared	-0.000155	Mean dependent var	0.005851
Adjusted R-squared	-0.000155	S.D. dependent var	0.063615
S.E. of regression	0.063620	Akaike info criterion	-2.848264
Sum squared resid	0.769023	Schwarz criterion	-2.797181
Log likelihood	275.0092	Hannan-Quinn criter.	-2.827573
Durbin-Watson stat	2.611326		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003555	0.002759	1.288403	0.1976
	Variance Equation			
C	0.001554	0.000217	7.146985	0.0000
RESID(-1)^2	0.316353	0.117973	2.681563	0.0073

R-squared	-0.000679	Mean dependent var	0.002329
Adjusted R-squared	-0.000679	S.D. dependent var	0.047207
S.E. of regression	0.047223	Akaike info criterion	-3.303842
Sum squared resid	0.423702	Schwarz criterion	-3.252759
Log likelihood	318.5169	Hannan-Quinn criter.	-3.283151
Durbin-Watson stat	2.726182		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.004320	0.009726	-0.444142	0.6569
	Variance Equation			
C	0.018120	0.001879	9.641368	0.0000
RESID(-1)^2	0.920301	0.145268	6.335188	0.0000
GARCH(-1)	-0.046204	0.019873	-2.324995	0.0201

R-squared	-0.000630	Mean dependent var	0.001967
Adjusted R-squared	-0.000630	S.D. dependent var	0.251155
S.E. of regression	0.251234	Akaike info criterion	-0.539359
Sum squared resid	11.99256	Schwarz criterion	-0.471248
Log likelihood	55.50876	Hannan-Quinn criter.	-0.511771
Durbin-Watson stat	3.269801		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004853	0.003323	1.460386	0.1442
	Variance Equation			
C	0.002168	0.000168	12.89700	0.0000
RESID(-1)^2	0.255443	0.095988	2.661204	0.0078

R-squared	-0.000051	Mean dependent var	0.004458
Adjusted R-squared	-0.000051	S.D. dependent var	0.055261
S.E. of regression	0.055263	Akaike info criterion	-3.040548
Sum squared resid	0.580256	Schwarz criterion	-2.989465
Log likelihood	293.3724	Hannan-Quinn criter.	-3.019857
Durbin-Watson stat	2.902773		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003550	0.006044	0.587352	0.5570
	Variance Equation			
C	0.006448	0.000701	9.199910	0.0000
RESID(-1)^2	0.181554	0.101381	1.790813	0.0733

R-squared	-0.000002	Mean dependent var	0.003437
Adjusted R-squared	-0.000002	S.D. dependent var	0.089113
S.E. of regression	0.089113	Akaike info criterion	-2.003470
Sum squared resid	1.508810	Schwarz criterion	-1.952387
Log likelihood	194.3313	Hannan-Quinn criter.	-1.982779
Durbin-Watson stat	2.460858		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008127	0.011564	0.702764	0.4822
Variance Equation				
C	0.010279	0.003306	3.109691	0.0019
RESID(-1)^2	0.416767	0.124080	3.358844	0.0008
GARCH(-1)	0.316185	0.120768	2.618124	0.0088

R-squared	-0.000144	Mean dependent var	0.010403
Adjusted R-squared	-0.000144	S.D. dependent var	0.189942
S.E. of regression	0.189956	Akaike info criterion	-0.715864
Sum squared resid	6.855810	Schwarz criterion	-0.647753
Log likelihood	72.36497	Hannan-Quinn criter.	-0.688276
Durbin-Watson stat	2.813972		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015356	0.007690	1.996881	0.0458
Variance Equation				
C	0.011028	0.001018	10.83355	0.0000
RESID(-1)^2	0.205045	0.113515	1.806329	0.0709

R-squared	-0.002651	Mean dependent var	0.009281
Adjusted R-squared	-0.002651	S.D. dependent var	0.118294
S.E. of regression	0.118451	Akaike info criterion	-1.450387
Sum squared resid	2.665805	Schwarz criterion	-1.399304
Log likelihood	141.5119	Hannan-Quinn criter.	-1.429696
Durbin-Watson stat	2.703797		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.019538	0.009310	2.098594	0.0359
Variance Equation				
C	0.015379	0.001738	8.849316	0.0000
RESID(-1)^2	0.509662	0.119031	4.281773	0.0000

R-squared	-0.004590	Mean dependent var	0.007650
Adjusted R-squared	-0.004590	S.D. dependent var	0.175940
S.E. of regression	0.176343	Akaike info criterion	-0.864419
Sum squared resid	5.908431	Schwarz criterion	-0.813336
Log likelihood	85.55204	Hannan-Quinn criter.	-0.843728
Durbin-Watson stat	2.977111		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.012690	0.007718	1.644101	0.1002
Variance Equation				
C	0.009783	0.001286	7.605577	0.0000
RESID(-1)^2	0.569083	0.143715	3.959793	0.0001

R-squared	-0.003484	Mean dependent var	0.004683
Adjusted R-squared	-0.003484	S.D. dependent var	0.135994
S.E. of regression	0.136230	Akaike info criterion	-1.282334
Sum squared resid	3.526157	Schwarz criterion	-1.231251
Log likelihood	125.4629	Hannan-Quinn criter.	-1.261643
Durbin-Watson stat	2.440802		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011835	0.005358	2.208808	0.0272
Variance Equation				
C	0.004736	0.000930	5.092486	0.0000
RESID(-1)^2	0.787739	0.168189	4.683639	0.0000

R-squared	-0.000768	Mean dependent var	0.008558
Adjusted R-squared	-0.000768	S.D. dependent var	0.118516
S.E. of regression	0.118561	Akaike info criterion	-1.772148
Sum squared resid	2.670787	Schwarz criterion	-1.721065
Log likelihood	172.2401	Hannan-Quinn criter.	-1.751457
Durbin-Watson stat	2.819965		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003222	0.004314	0.747053	0.4550
Variance Equation				
C	0.004683	0.000672	6.968957	0.0000
RESID(-1)^2	0.338260	0.108387	3.120848	0.0018
GARCH(-1)	-0.235036	0.097947	-2.399632	0.0164

R-squared	-0.000122	Mean dependent var	0.002426
Adjusted R-squared	-0.000122	S.D. dependent var	0.072311
S.E. of regression	0.072315	Akaike info criterion	-2.489979
Sum squared resid	0.993606	Schwarz criterion	-2.421868
Log likelihood	241.7929	Hannan-Quinn criter.	-2.462391
Durbin-Watson stat	2.903401		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010654	0.007096	1.501540	0.1332
		Variance Equation		
C	0.012561	0.001922	6.536096	0.0000
RESID(-1)^2	1.184977	0.155179	7.636202	0.0000

R-squared	-0.000219	Mean dependent var	0.006638
Adjusted R-squared	-0.000219	S.D. dependent var	0.272116
S.E. of regression	0.272146	Akaike info criterion	-0.537940
Sum squared resid	14.07208	Schwarz criterion	-0.486858
Log likelihood	54.37331	Hannan-Quinn criter.	-0.517249
Durbin-Watson stat	3.198317		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005939	0.003789	1.567201	0.1171
		Variance Equation		
C	0.002725	0.000263	10.34597	0.0000
RESID(-1)^2	0.299064	0.111743	2.676343	0.0074

R-squared	-0.000001	Mean dependent var	0.005988
Adjusted R-squared	-0.000001	S.D. dependent var	0.062429
S.E. of regression	0.062429	Akaike info criterion	-2.773397
Sum squared resid	0.740505	Schwarz criterion	-2.722315
Log likelihood	267.8594	Hannan-Quinn criter.	-2.752706
Durbin-Watson stat	2.924333		

Dependent Variable: ROP_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.025581	0.013194	1.938873	0.0525
		Variance Equation		
C	0.026738	0.002442	10.94850	0.0000
RESID(-1)^2	0.444220	0.152216	2.918347	0.0035

R-squared	-0.007350	Mean dependent var	0.006713
Adjusted R-squared	-0.007350	S.D. dependent var	0.220666
S.E. of regression	0.221475	Akaike info criterion	-0.363353
Sum squared resid	9.319743	Schwarz criterion	-0.312270
Log likelihood	37.70022	Hannan-Quinn criter.	-0.342662
Durbin-Watson stat	2.973323		

Appendix G - EViews outputs for ARCH/GARCH models with lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_BRAZIL_SA(-1)	-0.459836	0.077577	-5.927458	0.0000
RCB_BRAZIL_SA(-2)	-0.255411	0.074001	-3.451455	0.0006
C	0.026594	0.013029	2.041121	0.0412
Variance Equation				
C	0.002676	0.001572	1.702470	0.0887
RESID(-1)^2	0.163738	0.059866	2.735067	0.0062
GARCH(-1)	0.779005	0.072907	10.68488	0.0000

R-squared	0.172526	Mean dependent var	0.009428
Adjusted R-squared	0.163628	S.D. dependent var	0.237340
S.E. of regression	0.217056	Akaike info criterion	-0.333692
Sum squared resid	8.763048	Schwarz criterion	-0.230779
Log likelihood	37.53389	Hannan-Quinn criter.	-0.292000
Durbin-Watson stat	2.016435		

Dependent Variable: RCB_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 31 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_FRANCE_SA(-1)	-0.747544	0.038357	-19.48935	0.0000
RCB_FRANCE_SA(-2)	-0.470814	0.068543	-6.868834	0.0000
RCB_FRANCE_SA(-3)	-0.291579	0.071897	-4.055495	0.0001
Variance Equation				
C	0.035035	0.003324	10.54090	0.0000
RESID(-1)^2	-0.076346	0.051192	-1.491376	0.1359

R-squared	0.372630	Mean dependent var	0.002530
Adjusted R-squared	0.365848	S.D. dependent var	0.231949
S.E. of regression	0.184709	Akaike info criterion	-0.529654
Sum squared resid	6.311741	Schwarz criterion	-0.443578
Log likelihood	54.78744	Hannan-Quinn criter.	-0.494779
Durbin-Watson stat	2.082144		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_GERMANY_SA(-1)	-0.612832	0.091630	-6.688137	0.0000
RCB_GERMANY_SA(-2)	-0.425346	0.078072	-5.448142	0.0000
RCB_GERMANY_SA(-3)	-0.211730	0.086173	-2.457039	0.0140
Variance Equation				
C	0.039056	0.003382	11.54939	0.0000
RESID(-1)^2	-0.004499	0.051086	-0.088062	0.9298

R-squared	0.285103	Mean dependent var	0.000914
Adjusted R-squared	0.277374	S.D. dependent var	0.233834
S.E. of regression	0.198777	Akaike info criterion	-0.356245
Sum squared resid	7.309745	Schwarz criterion	-0.270170
Log likelihood	38.48705	Hannan-Quinn criter.	-0.321371
Durbin-Watson stat	2.040262		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2 + C(9)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_ITALY_SA(-1)	-0.729020	0.085357	-8.540828	0.0000
RCB_ITALY_SA(-2)	-0.513435	0.104718	-4.903005	0.0000
RCB_ITALY_SA(-3)	-0.356747	0.105702	-3.375018	0.0007
RCB_ITALY_SA(-4)	-0.258740	0.096829	-2.672137	0.0075
RCB_ITALY_SA(-5)	-0.180178	0.088781	-2.029462	0.0424
RCB_ITALY_SA(-6)	-0.138088	0.068742	-2.008781	0.0446
Variance Equation				
C	0.005664	0.006873	0.824068	0.4099
RESID(-1)^2	0.022973	0.030192	0.760900	0.4467
GARCH(-1)	0.828074	0.192368	4.304642	0.0000

R-squared	0.365699	Mean dependent var	6.83E-05
Adjusted R-squared	0.347981	S.D. dependent var	0.250023
S.E. of regression	0.201888	Akaike info criterion	-0.307547
Sum squared resid	7.295795	Schwarz criterion	-0.150881
Log likelihood	37.44806	Hannan-Quinn criter.	-0.244054
Durbin-Watson stat	2.043830		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_OTHERS_SA(-1)	-0.391018	0.081602	-4.791783	0.0000
RCB_OTHERS_SA(-2)	-0.345390	0.078109	-4.421926	0.0000
RCB_OTHERS_SA(-3)	-0.163087	0.077433	-2.106178	0.0352
RCB_OTHERS_SA(-5)	-0.145554	0.059512	-2.445805	0.0145
Variance Equation				
C	0.018418	0.001887	9.763087	0.0000
RESID(-1)^2	0.129728	0.096289	1.347278	0.1779

R-squared	0.205198	Mean dependent var	0.004022
Adjusted R-squared	0.192097	S.D. dependent var	0.163711
S.E. of regression	0.147149	Akaike info criterion	-0.970809
Sum squared resid	3.940816	Schwarz criterion	-0.866752
Log likelihood	96.28521	Hannan-Quinn criter.	-0.928641
Durbin-Watson stat	2.191341		

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_PORTUGAL_SA(-1)	-0.392057	0.076371	-5.133592	0.0000
RCB_PORTUGAL_SA(-2)	-0.249664	0.048752	-5.121058	0.0000
RCB_PORTUGAL_SA(-4)	-0.193956	0.063455	-3.056589	0.0022
Variance Equation				
C	0.004577	0.000638	7.173951	0.0000
RESID(-1)^2	0.379210	0.137508	2.757724	0.0058

R-squared	0.234993	Mean dependent var	0.002761
Adjusted R-squared	0.226678	S.D. dependent var	0.097089
S.E. of regression	0.085379	Akaike info criterion	-2.146802
Sum squared resid	1.341266	Schwarz criterion	-2.060409
Log likelihood	205.7260	Hannan-Quinn criter.	-2.111795
Durbin-Watson stat	2.150275		

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(8) + C(9)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_SPAIN_SA(-1)	-0.810253	0.084888	-9.544923	0.0000
RCB_SPAIN_SA(-2)	-0.778430	0.116569	-6.677875	0.0000
RCB_SPAIN_SA(-3)	-0.591582	0.132719	-4.457389	0.0000
RCB_SPAIN_SA(-4)	-0.448784	0.130796	-3.431187	0.0006
RCB_SPAIN_SA(-5)	-0.386152	0.126417	-3.054594	0.0023
RCB_SPAIN_SA(-6)	-0.333380	0.090605	-3.679488	0.0002
RCB_SPAIN_SA(-7)	-0.182132	0.061852	-2.944624	0.0032
Variance Equation				
C	0.030595	0.003623	8.445723	0.0000
RESID(-1)^2	0.483605	0.170084	2.843330	0.0045

R-squared	0.512493	Mean dependent var	0.001825
Adjusted R-squared	0.495967	S.D. dependent var	0.354168
S.E. of regression	0.251443	Akaike info criterion	-0.150624
Sum squared resid	11.19056	Schwarz criterion	0.006628
Log likelihood	22.85740	Hannan-Quinn criter.	-0.086888
Durbin-Watson stat	2.528028		

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_TOTAL_SA(-1)	-0.463886	0.068470	-6.775040	0.0000
RCB_TOTAL_SA(-2)	-0.336989	0.058081	-5.802074	0.0000
Variance Equation				
C	0.003592	0.000523	6.866479	0.0000
RESID(-1)^2	0.423494	0.139495	3.035909	0.0024

R-squared	0.229532	Mean dependent var	0.003022
Adjusted R-squared	0.225412	S.D. dependent var	0.086075
S.E. of regression	0.075755	Akaike info criterion	-2.378755
Sum squared resid	1.073173	Schwarz criterion	-2.310147
Log likelihood	228.7924	Hannan-Quinn criter.	-2.350960
Durbin-Watson stat	2.024059		

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_UK_SA(-1)	-0.591588	0.089872	-6.582532	0.0000
RCB_UK_SA(-2)	-0.276103	0.079107	-3.490227	0.0005
RCB_UK_SA(-3)	-0.310428	0.078643	-3.947324	0.0001
RCB_UK_SA(-4)	-0.193709	0.081272	-2.383453	0.0172
RCB_UK_SA(-5)	-0.153978	0.076659	-2.008602	0.0446
RCB_UK_SA(-6)	-0.168669	0.073871	-2.283279	0.0224
		Variance Equation		
C	0.033276	0.004539	7.331138	0.0000
RESID(-1)^2	0.312577	0.111096	2.813566	0.0049

R-squared	0.316569	Mean dependent var	0.001506
Adjusted R-squared	0.297479	S.D. dependent var	0.265361
S.E. of regression	0.222417	Akaike info criterion	-0.189165
Sum squared resid	8.854970	Schwarz criterion	-0.049906
Log likelihood	25.49776	Hannan-Quinn criter.	-0.132727
Durbin-Watson stat	2.056844		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_BRAZIL_SA(-1)	-0.306133	0.089735	-3.411515	0.0006
RLX_BRAZIL_SA(-2)	-0.195417	0.065653	-2.976514	0.0029
		Variance Equation		
C	0.010058	0.000861	11.68438	0.0000
RESID(-1)^2	0.421344	0.119419	3.528270	0.0004

R-squared	0.148478	Mean dependent var	0.007812
Adjusted R-squared	0.143924	S.D. dependent var	0.139894
S.E. of regression	0.129436	Akaike info criterion	-1.376604
Sum squared resid	3.132935	Schwarz criterion	-1.307996
Log likelihood	134.0891	Hannan-Quinn criter.	-1.348809
Durbin-Watson stat	2.235651		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_FRANCE_SA(-1)	-0.507770	0.088158	-5.759751	0.0000
RLX_FRANCE_SA(-2)	-0.172810	0.059378	-2.910364	0.0036
C	0.014369	0.006217	2.311466	0.0208
		Variance Equation		
C	0.005605	0.000413	13.57595	0.0000
RESID(-1)^2	0.065806	0.094398	0.697118	0.4857

R-squared	0.248156	Mean dependent var	0.007824
Adjusted R-squared	0.240072	S.D. dependent var	0.089919
S.E. of regression	0.078386	Akaike info criterion	-2.231578
Sum squared resid	1.142845	Schwarz criterion	-2.145818
Log likelihood	215.8842	Hannan-Quinn criter.	-2.196835
Durbin-Watson stat	2.115343		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_GERMANY_SA(-1)	-0.461772	0.076665	-6.023272	0.0000
RLX_GERMANY_SA(-2)	-0.278047	0.071827	-3.871093	0.0001
RLX_GERMANY_SA(-3)	-0.204416	0.068613	-2.979279	0.0029
RLX_GERMANY_SA(-4)	-0.152321	0.061581	-2.473480	0.0134
		Variance Equation		
C	0.006111	0.000931	6.561708	0.0000
RESID(-1)^2	0.206253	0.126365	1.632195	0.1026

R-squared	0.194240	Mean dependent var	0.004713
Adjusted R-squared	0.181031	S.D. dependent var	0.097687
S.E. of regression	0.088404	Akaike info criterion	-2.000218
Sum squared resid	1.430191	Schwarz criterion	-1.896547
Log likelihood	193.0204	Hannan-Quinn criter.	-1.958211
Durbin-Watson stat	2.061153		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_PORTUGAL_SA(-1)	-0.420137	0.080204	-5.238371	0.0000
RLX_PORTUGAL_SA(-2)	-0.193135	0.070280	-2.748054	0.0060
		Variance Equation		
C	0.001577	0.000216	7.312013	0.0000
RESID(-1)^2	0.167008	0.104318	1.600952	0.1094

R-squared	0.157440	Mean dependent var	0.002269
Adjusted R-squared	0.152935	S.D. dependent var	0.047454
S.E. of regression	0.043675	Akaike info criterion	-3.413120
Sum squared resid	0.356697	Schwarz criterion	-3.344512
Log likelihood	326.5398	Hannan-Quinn criter.	-3.385325
Durbin-Watson stat	2.053905		

Dependent Variable: RLX_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_ITALY_SA(-1)	-0.537748	0.074406	-7.227175	0.0000
RLX_ITALY_SA(-2)	-0.342042	0.069585	-4.915440	0.0000
		Variance Equation		
C	0.001537	0.001251	1.227930	0.2195
RESID(-1)^2	0.012786	0.050707	0.252152	0.8009
GARCH(-1)	0.830301	0.128960	6.438428	0.0000

R-squared	0.263299	Mean dependent var	0.002869
Adjusted R-squared	0.259359	S.D. dependent var	0.119055
S.E. of regression	0.102459	Akaike info criterion	-1.693248
Sum squared resid	1.963098	Schwarz criterion	-1.607487
Log likelihood	165.0119	Hannan-Quinn criter.	-1.658504
Durbin-Watson stat	2.032237		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M03 2016M12
Included observations: 190 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_OTHERS_SA(-1)	-0.211544	0.076280	-2.773269	0.0055
		Variance Equation		
C	0.001906	0.000257	7.425183	0.0000
RESID(-1)^2	0.533149	0.159495	3.342738	0.0008

R-squared	0.072108	Mean dependent var	0.006077
Adjusted R-squared	0.072108	S.D. dependent var	0.063706
S.E. of regression	0.061366	Akaike info criterion	-2.895827
Sum squared resid	0.711737	Schwarz criterion	-2.844559
Log likelihood	278.1036	Hannan-Quinn criter.	-2.875059
Durbin-Watson stat	2.266862		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_SPAIN_SA(-1)	-0.819053	0.087577	-9.352369	0.0000
RLX_SPAIN_SA(-2)	-0.467376	0.068325	-6.840491	0.0000
RLX_SPAIN_SA(-3)	-0.194885	0.052086	-3.741631	0.0002
		Variance Equation		
C	0.015068	0.001423	10.59105	0.0000
RESID(-1)^2	0.601074	0.147018	4.088433	0.0000

R-squared	0.534364	Mean dependent var	0.002392
Adjusted R-squared	0.529330	S.D. dependent var	0.252933
S.E. of regression	0.173525	Akaike info criterion	-0.872877
Sum squared resid	5.570547	Schwarz criterion	-0.786801
Log likelihood	87.05041	Hannan-Quinn criter.	-0.838002
Durbin-Watson stat	2.436708		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_TOTAL_SA(-1)	-0.556001	0.082366	-6.750341	0.0000
RLX_TOTAL_SA(-2)	-0.285960	0.067786	-4.218590	0.0000
C	0.008363	0.003550	2.355473	0.0185
		Variance Equation		
C	0.002001	0.000180	11.13759	0.0000
RESID(-1)^2	0.096689	0.079608	1.214561	0.2245

R-squared	0.280508	Mean dependent var	0.004378
Adjusted R-squared	0.272772	S.D. dependent var	0.055522
S.E. of regression	0.047348	Akaike info criterion	-3.235893
Sum squared resid	0.416981	Schwarz criterion	-3.150132
Log likelihood	310.7919	Hannan-Quinn criter.	-3.201149
Durbin-Watson stat	2.120677		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_UK_SA(-1)	-0.298352	0.074191	-4.021399	0.0001
RLX_UK_SA(-2)	-0.202765	0.076834	-2.639017	0.0083
RLX_UK_SA(-3)	-0.196365	0.077987	-2.517920	0.0118
		Variance Equation		
C	0.000939	0.000870	1.079378	0.2804
RESID(-1)^2	0.057211	0.049295	1.160593	0.2458
GARCH(-1)	0.806940	0.130951	6.162174	0.0000

R-squared	0.093598	Mean dependent var	0.004140
Adjusted R-squared	0.083799	S.D. dependent var	0.088888
S.E. of regression	0.085082	Akaike info criterion	-2.055898
Sum squared resid	1.339204	Schwarz criterion	-1.952607
Log likelihood	199.2544	Hannan-Quinn criter.	-2.014049
Durbin-Watson stat	1.946709		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_BRAZIL_SA(-1)	-0.449750	0.085270	-5.274391	0.0000
ROP_BRAZIL_SA(-2)	-0.283161	0.082882	-3.416438	0.0006
ROP_BRAZIL_SA(-3)	-0.126662	0.063594	-1.991731	0.0464
Variance Equation				
C	0.020680	0.001581	13.08411	0.0000
RESID(-1)^2	0.216719	0.085159	2.544882	0.0109

R-squared	0.229835	Mean dependent var	0.010343
Adjusted R-squared	0.221509	S.D. dependent var	0.191328
S.E. of regression	0.168813	Akaike info criterion	-0.793053
Sum squared resid	5.272092	Schwarz criterion	-0.706978
Log likelihood	79.54699	Hannan-Quinn criter.	-0.758179
Durbin-Watson stat	2.222878		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_FRANCE_SA(-1)	-0.431107	0.069303	-6.220611	0.0000
ROP_FRANCE_SA(-2)	-0.131172	0.066035	-1.986407	0.0470
Variance Equation				
C	0.003088	0.003276	0.942481	0.3459
RESID(-1)^2	-0.035777	0.036607	-0.977325	0.3284
GARCH(-1)	0.773373	0.267692	2.889045	0.0039

R-squared	0.136125	Mean dependent var	0.011038
Adjusted R-squared	0.131505	S.D. dependent var	0.117522
S.E. of regression	0.109522	Akaike info criterion	-1.551179
Sum squared resid	2.243096	Schwarz criterion	-1.465418
Log likelihood	151.5864	Hannan-Quinn criter.	-1.516435
Durbin-Watson stat	1.963446		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_GERMANY_SA(-1)	-0.601458	0.090268	-6.663053	0.0000
ROP_GERMANY_SA(-2)	-0.351956	0.110812	-3.176157	0.0015
ROP_GERMANY_SA(-3)	-0.271152	0.091999	-2.947344	0.0032
ROP_GERMANY_SA(-4)	-0.270602	0.078338	-3.454286	0.0006
ROP_GERMANY_SA(-5)	-0.156291	0.071330	-2.191105	0.0284
ROP_GERMANY_SA(-7)	0.146634	0.055187	2.657018	0.0079
Variance Equation				
C	0.014695	0.001539	9.549839	0.0000
RESID(-1)^2	0.253002	0.088843	2.847754	0.0044

R-squared	0.365735	Mean dependent var	0.006919
Adjusted R-squared	0.347919	S.D. dependent var	0.172735
S.E. of regression	0.139486	Akaike info criterion	-1.089464
Sum squared resid	3.463224	Schwarz criterion	-0.949684
Log likelihood	108.2307	Hannan-Quinn criter.	-1.032810
Durbin-Watson stat	2.123589		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_ITALY_SA(-1)	-0.137418	0.064425	-2.132992	0.0329
ROP_ITALY_SA(-2)	-0.156417	0.069879	-2.238389	0.0252
ROP_ITALY_SA(-3)	-0.161219	0.070549	-2.285213	0.0223
ROP_ITALY_SA(-4)	-0.145178	0.086027	-1.687590	0.0915
Variance Equation				
C	0.010175	0.001358	7.495697	0.0000
RESID(-1)^2	0.451233	0.124126	3.635275	0.0003

R-squared	0.087255	Mean dependent var	0.006169
Adjusted R-squared	0.072292	S.D. dependent var	0.136594
S.E. of regression	0.131564	Akaike info criterion	-1.306251
Sum squared resid	3.167546	Schwarz criterion	-1.202579
Log likelihood	128.1345	Hannan-Quinn criter.	-1.264244
Durbin-Watson stat	2.333549		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_OTHERS_SA(-1)	-0.457883	0.094795	-4.830250	0.0000
ROP_OTHERS_SA(-2)	-0.226413	0.069820	-3.242812	0.0012
C	0.016905	0.006200	2.726555	0.0064
Variance Equation				
C	0.005419	0.000786	6.893107	0.0000
RESID(-1)^2	0.528705	0.104285	5.069803	0.0000

R-squared	0.218047	Mean dependent var	0.008114
Adjusted R-squared	0.209639	S.D. dependent var	0.119027
S.E. of regression	0.105818	Akaike info criterion	-1.874627
Sum squared resid	2.082719	Schwarz criterion	-1.788866
Log likelihood	182.1522	Hannan-Quinn criter.	-1.839883
Durbin-Watson stat	2.156748		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 48 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_PORTUGAL_SA(-1)	-0.517142	0.052815	-9.791489	0.0000
ROP_PORTUGAL_SA(-2)	-0.206379	0.058970	-3.499709	0.0005
Variance Equation				
C	0.000331	7.26E-05	4.554197	0.0000
RESID(-1)^2	-0.056846	0.010558	-5.384374	0.0000
GARCH(-1)	0.976747	0.014886	65.61534	0.0000

R-squared	0.252583	Mean dependent var	0.002378
Adjusted R-squared	0.248586	S.D. dependent var	0.072276
S.E. of regression	0.062652	Akaike info criterion	-2.736374
Sum squared resid	0.734017	Schwarz criterion	-2.650614
Log likelihood	263.5874	Hannan-Quinn criter.	-2.701631
Durbin-Watson stat	2.139187		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 25 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_SPAIN_SA(-1)	-0.732337	0.068895	-10.62971	0.0000
ROP_SPAIN_SA(-2)	-0.457249	0.073484	-6.222446	0.0000
ROP_SPAIN_SA(-3)	-0.285416	0.063640	-4.484861	0.0000
ROP_SPAIN_SA(-4)	-0.120964	0.046378	-2.608215	0.0091
C	0.018225	0.007779	2.343006	0.0191
Variance Equation				
C	0.008909	0.001545	5.767832	0.0000
RESID(-1)^2	1.084414	0.198734	5.456606	0.0000

R-squared	0.492245	Mean dependent var	0.008204
Adjusted R-squared	0.481086	S.D. dependent var	0.274288
S.E. of regression	0.197585	Akaike info criterion	-0.939197
Sum squared resid	7.105276	Schwarz criterion	-0.818246
Log likelihood	94.81492	Hannan-Quinn criter.	-0.890188
Durbin-Watson stat	2.569082		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_TOTAL_SA(-1)	-0.530376	0.091359	-5.805404	0.0000
ROP_TOTAL_SA(-2)	-0.164150	0.078462	-2.092107	0.0364
C	0.010503	0.004219	2.489455	0.0128
Variance Equation				
C	0.002574	0.000247	10.42433	0.0000
RESID(-1)^2	0.119999	0.103558	1.158758	0.2466

R-squared	0.241457	Mean dependent var	0.005956
Adjusted R-squared	0.233301	S.D. dependent var	0.062289
S.E. of regression	0.054541	Akaike info criterion	-2.961678
Sum squared resid	0.553300	Schwarz criterion	-2.875918
Log likelihood	284.8786	Hannan-Quinn criter.	-2.926935
Durbin-Watson stat	2.057371		

Dependent Variable: ROP_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_UK_SA(-1)	-0.542513	0.075333	-7.201498	0.0000
ROP_UK_SA(-2)	-0.207941	0.073277	-2.837745	0.0045
ROP_UK_SA(-3)	-0.157261	0.062516	-2.515542	0.0119
C	0.026410	0.012281	2.150427	0.0315
Variance Equation				
C	0.000241	0.000456	0.529514	0.5964
RESID(-1)^2	0.052266	0.021448	2.436870	0.0148
GARCH(-1)	0.937260	0.025736	36.41814	0.0000

R-squared	0.290077	Mean dependent var	0.007461
Adjusted R-squared	0.278502	S.D. dependent var	0.216567
S.E. of regression	0.183954	Akaike info criterion	-0.599593
Sum squared resid	6.226416	Schwarz criterion	-0.479087
Log likelihood	63.36176	Hannan-Quinn criter.	-0.550769
Durbin-Watson stat	2.191170		

Appendix H - EViews outputs for EGARCH models without lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020420	0.014945	1.366366	0.1718
Variance Equation				
C(2)	-1.408229	0.330838	-4.256553	0.0000
C(3)	0.673831	0.164337	4.100294	0.0000
C(4)	-0.046140	0.121201	-0.380692	0.7034
C(5)	0.709006	0.090014	7.876600	0.0000

R-squared	-0.001723	Mean dependent var	0.010582
Adjusted R-squared	-0.001723	S.D. dependent var	0.237659
S.E. of regression	0.237863	Akaike info criterion	-0.153508
Sum squared resid	10.75002	Schwarz criterion	-0.068370
Log likelihood	19.66001	Hannan-Quinn criter.	-0.119023
Durbin-Watson stat	2.714687		

Dependent Variable: RCB_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005163	0.012003	0.430123	0.6671
Variance Equation				
C(2)	-3.721645	0.121374	-30.66252	0.0000
C(3)	0.772244	0.173565	4.449321	0.0000
C(4)	-0.006956	0.104210	-0.066747	0.9468

R-squared	-0.000098	Mean dependent var	0.002887
Adjusted R-squared	-0.000098	S.D. dependent var	0.230641
S.E. of regression	0.230653	Akaike info criterion	-0.250383
Sum squared resid	10.10813	Schwarz criterion	-0.182273
Log likelihood	27.91161	Hannan-Quinn criter.	-0.222795
Durbin-Watson stat	3.000818		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005046	0.014648	0.344503	0.7305
Variance Equation				
C(2)	-2.443573	0.369583	-6.611706	0.0000
C(3)	0.865361	0.201863	4.286869	0.0000
C(4)	0.202566	0.136759	1.481191	0.1386
C(5)	0.420208	0.109329	3.843517	0.0001

R-squared	-0.000654	Mean dependent var	-0.000923
Adjusted R-squared	-0.000654	S.D. dependent var	0.233956
S.E. of regression	0.234033	Akaike info criterion	-0.187567
Sum squared resid	10.40655	Schwarz criterion	-0.102429
Log likelihood	22.91262	Hannan-Quinn criter.	-0.153082
Durbin-Watson stat	2.800336		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.003535	0.013055	-0.270805	0.7865
Variance Equation				
C(2)	-5.035806	0.343419	-14.66373	0.0000
C(3)	0.525526	0.143462	3.663169	0.0002
C(4)	0.003509	0.038456	0.091254	0.9273
C(5)	-0.592031	0.106821	-5.542274	0.0000

R-squared	-0.000218	Mean dependent var	0.000119
Adjusted R-squared	-0.000218	S.D. dependent var	0.248254
S.E. of regression	0.248281	Akaike info criterion	-0.015744
Sum squared resid	11.71228	Schwarz criterion	0.069394
Log likelihood	6.503576	Hannan-Quinn criter.	0.018741
Durbin-Watson stat	2.979784		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010426	0.011355	0.918184	0.3585
		Variance Equation		
C(2)	-4.106024	0.153016	-26.83398	0.0000
C(3)	0.505469	0.173735	2.909426	0.0036
C(4)	0.044461	0.116105	0.382936	0.7018

R-squared	-0.001515	Mean dependent var	0.004136
Adjusted R-squared	-0.001515	S.D. dependent var	0.162017
S.E. of regression	0.162140	Akaike info criterion	-0.833742
Sum squared resid	4.994989	Schwarz criterion	-0.765632
Log likelihood	83.62239	Hannan-Quinn criter.	-0.806154
Durbin-Watson stat	2.603686		

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007452	0.005202	1.432457	0.1520
		Variance Equation		
C(2)	-4.224645	0.642316	-6.577202	0.0000
C(3)	0.982013	0.215544	4.555970	0.0000
C(4)	0.151016	0.145072	1.040972	0.2979
C(5)	0.293997	0.134991	2.177911	0.0294

R-squared	-0.002803	Mean dependent var	0.002364
Adjusted R-squared	-0.002803	S.D. dependent var	0.096354
S.E. of regression	0.096489	Akaike info criterion	-2.005363
Sum squared resid	1.768910	Schwarz criterion	-1.920225
Log likelihood	196.5122	Hannan-Quinn criter.	-1.970878
Durbin-Watson stat	2.722439		

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.025452	0.014349	1.773776	0.0761
		Variance Equation		
C(2)	-2.602661	0.375243	-6.935930	0.0000
C(3)	0.984829	0.135622	7.261591	0.0000
C(4)	0.209452	0.128838	1.625698	0.1040
C(5)	0.317827	0.121864	2.608057	0.0091

R-squared	-0.004796	Mean dependent var	0.001382
Adjusted R-squared	-0.004796	S.D. dependent var	0.348492
S.E. of regression	0.349327	Akaike info criterion	0.100497
Sum squared resid	23.18555	Schwarz criterion	0.185635
Log likelihood	-4.597427	Hannan-Quinn criter.	0.134981
Durbin-Watson stat	3.128904		

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003901	0.005545	0.703500	0.4817
		Variance Equation		
C(2)	-1.911019	0.812538	-2.351914	0.0187
C(3)	0.539567	0.176135	3.063372	0.0022
C(4)	0.138303	0.111351	1.242041	0.2142
C(5)	0.705007	0.148818	4.737370	0.0000

R-squared	-0.000101	Mean dependent var	0.003045
Adjusted R-squared	-0.000101	S.D. dependent var	0.085637
S.E. of regression	0.085641	Akaike info criterion	-2.201562
Sum squared resid	1.393528	Schwarz criterion	-2.116424
Log likelihood	215.2492	Hannan-Quinn criter.	-2.167077
Durbin-Watson stat	2.684296		

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000537	0.016014	0.033554	0.9732
	Variance Equation			
C(2)	-2.058779	0.417673	-4.929163	0.0000
C(3)	0.730068	0.191799	3.806413	0.0001
C(4)	-0.103084	0.115951	-0.889033	0.3740
C(5)	0.477823	0.143559	3.328410	0.0009

R-squared	-0.000096	Mean dependent var	0.003128
Adjusted R-squared	-0.000096	S.D. dependent var	0.264508
S.E. of regression	0.264521	Akaike info criterion	0.052439
Sum squared resid	13.29452	Schwarz criterion	0.137577
Log likelihood	-0.007964	Hannan-Quinn criter.	0.086924
Durbin-Watson stat	2.931285		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002274	0.008562	0.265605	0.7905
	Variance Equation			
C(2)	-6.160564	0.582695	-10.57254	0.0000
C(3)	0.678463	0.159768	4.246554	0.0000
C(4)	-0.154830	0.085866	-1.803165	0.0714
C(5)	-0.328630	0.142320	-2.309097	0.0209

R-squared	-0.002074	Mean dependent var	0.008606
Adjusted R-squared	-0.002074	S.D. dependent var	0.139406
S.E. of regression	0.139551	Akaike info criterion	-1.375616
Sum squared resid	3.700128	Schwarz criterion	-1.290478
Log likelihood	136.3713	Hannan-Quinn criter.	-1.341131
Durbin-Watson stat	2.661819		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006779	0.006865	0.987489	0.3234
	Variance Equation			
C(2)	-2.916278	0.471762	-6.181676	0.0000
C(3)	0.483037	0.108578	4.448742	0.0000
C(4)	-0.064773	0.108637	-0.596231	0.5510
C(5)	0.477474	0.090383	5.282785	0.0000

R-squared	-0.000057	Mean dependent var	0.006056
Adjusted R-squared	-0.000057	S.D. dependent var	0.096401
S.E. of regression	0.096403	Akaike info criterion	-1.982750
Sum squared resid	1.765785	Schwarz criterion	-1.897612
Log likelihood	194.3527	Hannan-Quinn criter.	-1.948266
Durbin-Watson stat	2.742384		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.014526	0.006858	2.118166	0.0342
	Variance Equation			
C(2)	-1.773432	0.552005	-3.212710	0.0013
C(3)	0.466145	0.148391	3.141334	0.0017
C(4)	0.255624	0.114889	2.224969	0.0261
C(5)	0.702599	0.112575	6.241179	0.0000

R-squared	-0.010700	Mean dependent var	0.004335
Adjusted R-squared	-0.010700	S.D. dependent var	0.098782
S.E. of regression	0.099310	Akaike info criterion	-1.861461
Sum squared resid	1.873852	Schwarz criterion	-1.776323
Log likelihood	182.7696	Hannan-Quinn criter.	-1.826976
Durbin-Watson stat	2.673777		

Dependent Variable: RLX_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006981	0.007614	0.916973	0.3592
Variance Equation				
C(2)	-4.805788	0.180059	-26.69003	0.0000
C(3)	0.585329	0.184993	3.164059	0.0016
C(4)	0.050887	0.127439	0.399303	0.6897

R-squared	-0.001072	Mean dependent var	0.003112
Adjusted R-squared	-0.001072	S.D. dependent var	0.118493
S.E. of regression	0.118556	Akaike info criterion	-1.481508
Sum squared resid	2.670553	Schwarz criterion	-1.413397
Log likelihood	145.4840	Hannan-Quinn criter.	-1.453920
Durbin-Watson stat	2.796072		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.014009	0.004011	3.492956	0.0005
Variance Equation				
C(2)	-3.277502	1.057632	-3.098905	0.0019
C(3)	0.513983	0.177118	2.901925	0.0037
C(4)	0.399365	0.116450	3.429499	0.0006
C(5)	0.498412	0.168112	2.964771	0.0030

R-squared	-0.016532	Mean dependent var	0.005851
Adjusted R-squared	-0.016532	S.D. dependent var	0.063615
S.E. of regression	0.064139	Akaike info criterion	-2.889887
Sum squared resid	0.781615	Schwarz criterion	-2.804749
Log likelihood	280.9842	Hannan-Quinn criter.	-2.855403
Durbin-Watson stat	2.569256		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003424	0.010223	0.334892	0.7377
Variance Equation				
C(2)	-3.381552	0.340890	-9.919767	0.0000
C(3)	1.243173	0.179628	6.920837	0.0000
C(4)	0.000169	0.155152	0.001088	0.9991
C(5)	0.289903	0.095605	3.032312	0.0024

R-squared	-0.000034	Mean dependent var	0.001967
Adjusted R-squared	-0.000034	S.D. dependent var	0.251155
S.E. of regression	0.251160	Akaike info criterion	-0.614832
Sum squared resid	11.98541	Schwarz criterion	-0.529693
Log likelihood	63.71641	Hannan-Quinn criter.	-0.580347
Durbin-Watson stat	3.271751		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002069	0.003027	0.683395	0.4944
Variance Equation				
C(2)	-6.619011	0.159866	-41.40355	0.0000
C(3)	0.551340	0.151452	3.640355	0.0003
C(4)	-0.082524	0.109479	-0.753791	0.4510

R-squared	-0.000031	Mean dependent var	0.002329
Adjusted R-squared	-0.000031	S.D. dependent var	0.047207
S.E. of regression	0.047208	Akaike info criterion	-3.301736
Sum squared resid	0.423428	Schwarz criterion	-3.233626
Log likelihood	319.3158	Hannan-Quinn criter.	-3.274148
Durbin-Watson stat	2.727948		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006373	0.003297	1.933228	0.0532
	Variance Equation			
C(2)	-6.268977	0.085913	-72.96867	0.0000
C(3)	0.490151	0.150176	3.263835	0.0011
C(4)	0.088381	0.111913	0.789729	0.4297

R-squared	-0.001207	Mean dependent var	0.004458
Adjusted R-squared	-0.001207	S.D. dependent var	0.055261
S.E. of regression	0.055295	Akaike info criterion	-3.039736
Sum squared resid	0.580927	Schwarz criterion	-2.971626
Log likelihood	294.2948	Hannan-Quinn criter.	-3.012148
Durbin-Watson stat	2.899423		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005908	0.006315	0.935451	0.3496
	Variance Equation			
C(2)	-5.139487	0.120177	-42.76593	0.0000
C(3)	0.335108	0.153200	2.187395	0.0287
C(4)	0.122872	0.114379	1.074254	0.2827

R-squared	-0.000773	Mean dependent var	0.003437
Adjusted R-squared	-0.000773	S.D. dependent var	0.089113
S.E. of regression	0.089147	Akaike info criterion	-2.003940
Sum squared resid	1.509974	Schwarz criterion	-1.935830
Log likelihood	195.3763	Hannan-Quinn criter.	-1.976352
Durbin-Watson stat	2.458961		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008721	0.011879	0.734091	0.4629
	Variance Equation			
C(2)	-1.924592	0.430293	-4.472747	0.0000
C(3)	0.664253	0.160389	4.141515	0.0000
C(4)	-0.111552	0.145226	-0.768130	0.4424
C(5)	0.604517	0.116765	5.177199	0.0000

R-squared	-0.000079	Mean dependent var	0.010403
Adjusted R-squared	-0.000079	S.D. dependent var	0.189942
S.E. of regression	0.189950	Akaike info criterion	-0.757348
Sum squared resid	6.855361	Schwarz criterion	-0.672210
Log likelihood	77.32672	Hannan-Quinn criter.	-0.722863
Durbin-Watson stat	2.814157		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011856	0.008604	1.377993	0.1682
	Variance Equation			
C(2)	-4.568601	0.105519	-43.29661	0.0000
C(3)	0.344508	0.171667	2.006838	0.0448
C(4)	-0.022268	0.118160	-0.188459	0.8505

R-squared	-0.000476	Mean dependent var	0.009281
Adjusted R-squared	-0.000476	S.D. dependent var	0.118294
S.E. of regression	0.118322	Akaike info criterion	-1.432993
Sum squared resid	2.660022	Schwarz criterion	-1.364883
Log likelihood	140.8508	Hannan-Quinn criter.	-1.405405
Durbin-Watson stat	2.709676		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.022658	0.009875	2.294388	0.0218
	Variance Equation			
C(2)	-4.309840	0.133309	-32.32962	0.0000
C(3)	0.771980	0.145815	5.294247	0.0000
C(4)	0.076160	0.091323	0.833965	0.4043

R-squared	-0.007315	Mean dependent var	0.007650
Adjusted R-squared	-0.007315	S.D. dependent var	0.175940
S.E. of regression	0.176582	Akaike info criterion	-0.864323
Sum squared resid	5.924461	Schwarz criterion	-0.796212
Log likelihood	86.54284	Hannan-Quinn criter.	-0.836735
Durbin-Watson stat	2.969056		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002989	0.007364	-0.405904	0.6848
	Variance Equation			
C(2)	-4.794700	0.159010	-30.15336	0.0000
C(3)	0.681558	0.176130	3.869635	0.0001
C(4)	-0.465031	0.089223	-5.212031	0.0000

R-squared	-0.003200	Mean dependent var	0.004683
Adjusted R-squared	-0.003200	S.D. dependent var	0.135994
S.E. of regression	0.136211	Akaike info criterion	-1.392174
Sum squared resid	3.525157	Schwarz criterion	-1.324064
Log likelihood	136.9526	Hannan-Quinn criter.	-1.364586
Durbin-Watson stat	2.441495		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.013335	0.005606	2.378609	0.0174
	Variance Equation			
C(2)	-5.553717	0.146645	-37.87174	0.0000
C(3)	1.044583	0.160755	6.497962	0.0000
C(4)	0.147976	0.105592	1.401392	0.1611

R-squared	-0.001633	Mean dependent var	0.008558
Adjusted R-squared	-0.001633	S.D. dependent var	0.118516
S.E. of regression	0.118612	Akaike info criterion	-1.849287
Sum squared resid	2.673095	Schwarz criterion	-1.781176
Log likelihood	180.6069	Hannan-Quinn criter.	-1.821699
Durbin-Watson stat	2.817530		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003455	0.004290	0.805391	0.4206
	Variance Equation			
C(2)	-5.796283	0.106662	-54.34257	0.0000
C(3)	0.585656	0.140398	4.171409	0.0000
C(4)	-0.011480	0.101954	-0.112599	0.9103

R-squared	-0.000204	Mean dependent var	0.002426
Adjusted R-squared	-0.000204	S.D. dependent var	0.072311
S.E. of regression	0.072318	Akaike info criterion	-2.474084
Sum squared resid	0.993688	Schwarz criterion	-2.405974
Log likelihood	240.2751	Hannan-Quinn criter.	-2.446497
Durbin-Watson stat	2.903163		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.022937	0.009226	2.486059	0.0129
		Variance Equation		
C(2)	-2.905232	0.465411	-6.242296	0.0000
C(3)	1.250028	0.197694	6.323030	0.0000
C(4)	0.151313	0.135729	1.114817	0.2649
C(5)	0.415821	0.111993	3.712901	0.0002

R-squared	-0.003606	Mean dependent var	0.006638
Adjusted R-squared	-0.003606	S.D. dependent var	0.272116
S.E. of regression	0.272607	Akaike info criterion	-0.530180
Sum squared resid	14.11974	Schwarz criterion	-0.445042
Log likelihood	55.63219	Hannan-Quinn criter.	-0.495695
Durbin-Watson stat	3.187522		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009690	0.003898	2.485994	0.0129
		Variance Equation		
C(2)	-6.106959	0.116802	-52.28453	0.0000
C(3)	0.585703	0.159631	3.669101	0.0002
C(4)	0.124215	0.119725	1.037500	0.2995

R-squared	-0.003535	Mean dependent var	0.005988
Adjusted R-squared	-0.003535	S.D. dependent var	0.062429
S.E. of regression	0.062539	Akaike info criterion	-2.792090
Sum squared resid	0.743123	Schwarz criterion	-2.723979
Log likelihood	270.6446	Hannan-Quinn criter.	-2.764502
Durbin-Watson stat	2.914035		

Dependent Variable: ROP_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020890	0.013115	1.592789	0.1112
		Variance Equation		
C(2)	-3.779241	0.087693	-43.09630	0.0000
C(3)	0.747706	0.174581	4.282852	0.0000
C(4)	-0.006054	0.139564	-0.043377	0.9654

R-squared	-0.004149	Mean dependent var	0.006713
Adjusted R-squared	-0.004149	S.D. dependent var	0.220666
S.E. of regression	0.221123	Akaike info criterion	-0.374046
Sum squared resid	9.290133	Schwarz criterion	-0.305935
Log likelihood	39.72136	Hannan-Quinn criter.	-0.346458
Durbin-Watson stat	2.982800		

Appendix I - EViews outputs for EGARCH models with lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_BRAZIL_SA(-1)	-0.497231	0.067012	-7.420037	0.0000
RCB_BRAZIL_SA(-2)	-0.318746	0.063753	-4.999713	0.0000
RCB_BRAZIL_SA(-3)	-0.144759	0.054875	-2.637987	0.0083
Variance Equation				
C(4)	-3.378406	0.144998	-23.29965	0.0000
C(5)	0.339835	0.187182	1.815533	0.0694
C(6)	-0.306117	0.084379	-3.627867	0.0003

R-squared	0.177339	Mean dependent var	0.009926
Adjusted R-squared	0.168445	S.D. dependent var	0.237875
S.E. of regression	0.216917	Akaike info criterion	-0.257852
Sum squared resid	8.704837	Schwarz criterion	-0.154561
Log likelihood	30.23808	Hannan-Quinn criter.	-0.216002
Durbin-Watson stat	1.948763		

Dependent Variable: RCB_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_FRANCE_SA(-1)	-0.735193	0.068551	-10.72484	0.0000
RCB_FRANCE_SA(-2)	-0.461874	0.091746	-5.034260	0.0000
RCB_FRANCE_SA(-3)	-0.244168	0.072268	-3.378634	0.0007
Variance Equation				
C(4)	-3.496377	0.188913	-18.50789	0.0000
C(5)	0.101352	0.227983	0.444561	0.6566
C(6)	-0.285928	0.093820	-3.047619	0.0023

R-squared	0.374226	Mean dependent var	0.002530
Adjusted R-squared	0.367461	S.D. dependent var	0.231949
S.E. of regression	0.184474	Akaike info criterion	-0.524993
Sum squared resid	6.295680	Schwarz criterion	-0.421702
Log likelihood	55.34930	Hannan-Quinn criter.	-0.483143
Durbin-Watson stat	2.089251		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_GERMANY_SA(-1)	-0.616249	0.087811	-7.017910	0.0000
RCB_GERMANY_SA(-2)	-0.429120	0.079757	-5.380339	0.0000
RCB_GERMANY_SA(-3)	-0.211252	0.087112	-2.425055	0.0153
Variance Equation				
C(4)	-3.213812	0.134778	-23.84515	0.0000
C(5)	-0.047033	0.161674	-0.290911	0.7711
C(6)	0.030298	0.081955	0.369690	0.7116

R-squared	0.285056	Mean dependent var	0.000914
Adjusted R-squared	0.277327	S.D. dependent var	0.233834
S.E. of regression	0.198783	Akaike info criterion	-0.346853
Sum squared resid	7.310221	Schwarz criterion	-0.243563
Log likelihood	38.60421	Hannan-Quinn criter.	-0.305004
Durbin-Watson stat	2.033435		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(5) + C(6)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(7)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_ITALY_SA(-1)	-0.722722	0.079374	-9.105291	0.0000
RCB_ITALY_SA(-2)	-0.485851	0.100168	-4.850336	0.0000
RCB_ITALY_SA(-3)	-0.297532	0.098227	-3.029007	0.0025
RCB_ITALY_SA(-4)	-0.123816	0.055096	-2.247260	0.0246
Variance Equation				
C(5)	-3.240300	0.123502	-26.23690	0.0000
C(6)	0.028382	0.183584	0.154601	0.8771
C(7)	0.121747	0.123961	0.982143	0.3260

R-squared	0.349351	Mean dependent var	-0.000593
Adjusted R-squared	0.338685	S.D. dependent var	0.249447
S.E. of regression	0.202854	Akaike info criterion	-0.306132
Sum squared resid	7.530393	Schwarz criterion	-0.185182
Log likelihood	35.62337	Hannan-Quinn criter.	-0.257123
Durbin-Watson stat	2.029128		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_OTHERS_SA(-1)	-0.316677	0.081612	-3.880284	0.0001
RCB_OTHERS_SA(-2)	-0.274208	0.064254	-4.267535	0.0000
RCB_OTHERS_SA(-5)	-0.146119	0.058368	-2.503408	0.0123
Variance Equation				
C(4)	-4.144231	0.137840	-30.06561	0.0000
C(5)	0.385462	0.155931	2.472001	0.0134
C(6)	-0.022384	0.100067	-0.223691	0.8230

R-squared	0.171499	Mean dependent var	0.004022
Adjusted R-squared	0.162444	S.D. dependent var	0.163711
S.E. of regression	0.149825	Akaike info criterion	-0.946177
Sum squared resid	4.107906	Schwarz criterion	-0.842121
Log likelihood	93.99448	Hannan-Quinn criter.	-0.904010
Durbin-Watson stat	2.284007		

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_PORTUGAL_SA(-1)	-0.416834	0.085134	-4.896181	0.0000
RCB_PORTUGAL_SA(-2)	-0.255362	0.057320	-4.455056	0.0000
RCB_PORTUGAL_SA(-4)	-0.214779	0.061561	-3.488877	0.0005
Variance Equation				
C(4)	-3.322414	0.806459	-4.119758	0.0000
C(5)	0.595288	0.180043	3.306357	0.0009
C(6)	0.187149	0.112609	1.661933	0.0965
C(7)	0.441513	0.155045	2.847644	0.0044

R-squared	0.238252	Mean dependent var	0.002761
Adjusted R-squared	0.229972	S.D. dependent var	0.097089
S.E. of regression	0.085196	Akaike info criterion	-2.178562
Sum squared resid	1.335552	Schwarz criterion	-2.057611
Log likelihood	210.6955	Hannan-Quinn criter.	-2.129553
Durbin-Watson stat	2.105771		

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 20 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(8) + C(9)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(10)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_SPAIN_SA(-1)	-0.850659	0.076357	-11.14059	0.0000
RCB_SPAIN_SA(-2)	-0.713104	0.113044	-6.308216	0.0000
RCB_SPAIN_SA(-3)	-0.529745	0.117756	-4.498667	0.0000
RCB_SPAIN_SA(-4)	-0.401389	0.121060	-3.315617	0.0009
RCB_SPAIN_SA(-5)	-0.333679	0.112609	-2.963155	0.0030
RCB_SPAIN_SA(-6)	-0.227093	0.081056	-2.801673	0.0051
RCB_SPAIN_SA(-7)	-0.148609	0.045292	-3.281116	0.0010
Variance Equation				
C(8)	-3.479012	0.170741	-20.37595	0.0000
C(9)	0.408254	0.219436	1.860469	0.0628
C(10)	0.403382	0.104694	3.852969	0.0001

R-squared	0.525387	Mean dependent var	0.001825
Adjusted R-squared	0.509298	S.D. dependent var	0.354168
S.E. of regression	0.248095	Akaike info criterion	-0.193983
Sum squared resid	10.89457	Schwarz criterion	-0.019259
Log likelihood	27.84646	Hannan-Quinn criter.	-0.123165
Durbin-Watson stat	2.421308		

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_TOTAL_SA(-1)	-0.513862	0.065280	-7.871697	0.0000
RCB_TOTAL_SA(-2)	-0.336036	0.061091	-5.500611	0.0000
Variance Equation				
C(3)	-5.646788	0.164931	-34.23737	0.0000
C(4)	0.456251	0.166670	2.737452	0.0062
C(5)	0.294550	0.092404	3.187641	0.0014

R-squared	0.226099	Mean dependent var	0.003022
Adjusted R-squared	0.221961	S.D. dependent var	0.086075
S.E. of regression	0.075924	Akaike info criterion	-2.389776
Sum squared resid	1.077955	Schwarz criterion	-2.304015
Log likelihood	230.8338	Hannan-Quinn criter.	-2.355032
Durbin-Watson stat	1.929397		

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(7) + C(8)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(9)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_UK_SA(-1)	-0.622510	0.086407	-7.204359	0.0000
RCB_UK_SA(-2)	-0.317664	0.071290	-4.455966	0.0000
RCB_UK_SA(-3)	-0.317069	0.074358	-4.264114	0.0000
RCB_UK_SA(-4)	-0.206720	0.077822	-2.656310	0.0079
RCB_UK_SA(-5)	-0.168580	0.079008	-2.133707	0.0329
RCB_UK_SA(-6)	-0.189472	0.069332	-2.732830	0.0063
Variance Equation				
C(7)	-3.547015	0.155054	-22.87600	0.0000
C(8)	0.546242	0.158552	3.445197	0.0006
C(9)	-0.203523	0.104381	-1.949814	0.0512

R-squared	0.314659	Mean dependent var	0.001506
Adjusted R-squared	0.295515	S.D. dependent var	0.265361
S.E. of regression	0.222727	Akaike info criterion	-0.188662
Sum squared resid	8.879720	Schwarz criterion	-0.031996
Log likelihood	26.45125	Hannan-Quinn criter.	-0.125169
Durbin-Watson stat	2.004579		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 27 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_BRAZIL_SA(-1)	-0.217780	0.070237	-3.100635	0.0019
RLX_BRAZIL_SA(-2)	-0.170950	0.054666	-3.127183	0.0018
Variance Equation				
C(3)	-6.500360	0.630832	-10.30442	0.0000
C(4)	0.602430	0.143052	4.211275	0.0000
C(5)	-0.117202	0.077461	-1.513033	0.1303
C(6)	-0.389596	0.149879	-2.599404	0.0093

R-squared	0.124573	Mean dependent var	0.007812
Adjusted R-squared	0.119891	S.D. dependent var	0.139894
S.E. of regression	0.131240	Akaike info criterion	-1.444027
Sum squared resid	3.220888	Schwarz criterion	-1.341115
Log likelihood	142.4606	Hannan-Quinn criter.	-1.402335
Durbin-Watson stat	2.400996		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_FRANCE_SA(-1)	-0.534064	0.069625	-7.670569	0.0000
RLX_FRANCE_SA(-2)	-0.148426	0.050258	-2.953285	0.0031
C	0.012506	0.005642	2.216536	0.0267
Variance Equation				
C(4)	-9.604450	0.551448	-17.41678	0.0000
C(5)	0.169771	0.101161	1.678219	0.0933
C(6)	-0.126280	0.070572	-1.789369	0.0736
C(7)	-0.847199	0.110544	-7.663941	0.0000

R-squared	0.247971	Mean dependent var	0.007824
Adjusted R-squared	0.239885	S.D. dependent var	0.089919
S.E. of regression	0.078395	Akaike info criterion	-2.234806
Sum squared resid	1.143125	Schwarz criterion	-2.114742
Log likelihood	218.1892	Hannan-Quinn criter.	-2.186165
Durbin-Watson stat	2.070557		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(5) + C(6)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(7)
*RESID(-1)/@SQRT(GARCH(-1)) + C(8)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_GERMANY_SA(-1)	-0.455373	0.084728	-5.374521	0.0000
RLX_GERMANY_SA(-2)	-0.257308	0.085473	-3.010410	0.0026
RLX_GERMANY_SA(-3)	-0.184150	0.084137	-2.188695	0.0286
RLX_GERMANY_SA(-4)	-0.139952	0.068237	-2.050966	0.0403
Variance Equation				
C(5)	-2.115792	1.273698	-1.661141	0.0967
C(6)	0.379294	0.193751	1.957637	0.0503
C(7)	0.017166	0.098262	0.174693	0.8613
C(8)	0.631139	0.237917	2.652772	0.0080

R-squared	0.193072	Mean dependent var	0.004713
Adjusted R-squared	0.179844	S.D. dependent var	0.097687
S.E. of regression	0.088468	Akaike info criterion	-2.001166
Sum squared resid	1.432263	Schwarz criterion	-1.862936
Log likelihood	195.1090	Hannan-Quinn criter.	-1.945155
Durbin-Watson stat	2.070241		

Dependent Variable: RLX_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 42 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_ITALY_SA(-1)	-0.527399	0.076984	-6.850751	0.0000
RLX_ITALY_SA(-2)	-0.327247	0.073293	-4.464938	0.0000
Variance Equation				
C(3)	-0.755889	0.701074	-1.078187	0.2810
C(4)	0.058342	0.117589	0.496153	0.6198
C(5)	-0.030677	0.051579	-0.594755	0.5520
C(6)	0.845734	0.154623	5.469670	0.0000

R-squared	0.262868	Mean dependent var	0.002869
Adjusted R-squared	0.258926	S.D. dependent var	0.119055
S.E. of regression	0.102489	Akaike info criterion	-1.683920
Sum squared resid	1.964247	Schwarz criterion	-1.581007
Log likelihood	165.1304	Hannan-Quinn criter.	-1.642227
Durbin-Watson stat	2.051672		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_OTHERS_SA(-1)	-0.293339	0.083169	-3.527017	0.0004
RLX_OTHERS_SA(-2)	-0.148211	0.060784	-2.438327	0.0148
C	0.010879	0.003905	2.786080	0.0053
Variance Equation				
C(4)	-3.201105	0.817922	-3.913706	0.0001
C(5)	0.371827	0.154300	2.409776	0.0160
C(6)	0.409221	0.101211	4.043259	0.0001
C(7)	0.502979	0.131618	3.821498	0.0001

R-squared	0.150554	Mean dependent var	0.005527
Adjusted R-squared	0.141420	S.D. dependent var	0.063422
S.E. of regression	0.058767	Akaike info criterion	-2.957041
Sum squared resid	0.642361	Schwarz criterion	-2.836976
Log likelihood	286.4404	Hannan-Quinn criter.	-2.908400
Durbin-Watson stat	2.159394		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_PORTUGAL_SA(-1)	-0.418436	0.075140	-5.568722	0.0000
RLX_PORTUGAL_SA(-2)	-0.190181	0.071774	-2.649735	0.0081
Variance Equation				
C(3)	-6.504419	0.157270	-41.35840	0.0000
C(4)	0.271590	0.150028	1.810266	0.0703
C(5)	-0.155839	0.098411	-1.583556	0.1133

R-squared	0.157472	Mean dependent var	0.002269
Adjusted R-squared	0.152966	S.D. dependent var	0.047454
S.E. of regression	0.043674	Akaike info criterion	-3.409971
Sum squared resid	0.356683	Schwarz criterion	-3.324211
Log likelihood	327.2423	Hannan-Quinn criter.	-3.375228
Durbin-Watson stat	2.056520		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_SPAIN_SA(-1)	-0.830660	0.054393	-15.27139	0.0000
RLX_SPAIN_SA(-2)	-0.480565	0.058653	-8.193387	0.0000
RLX_SPAIN_SA(-3)	-0.220069	0.051923	-4.238383	0.0000
Variance Equation				
C(4)	-5.745628	0.395559	-14.52532	0.0000
C(5)	0.542446	0.151022	3.591828	0.0003
C(6)	0.353605	0.111666	3.166622	0.0015
C(7)	-0.363220	0.095045	-3.821562	0.0001

R-squared	0.537778	Mean dependent var	0.002392
Adjusted R-squared	0.532781	S.D. dependent var	0.252933
S.E. of regression	0.172888	Akaike info criterion	-0.988340
Sum squared resid	5.529701	Schwarz criterion	-0.867835
Log likelihood	99.90399	Hannan-Quinn criter.	-0.939516
Durbin-Watson stat	2.419469		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_TOTAL_SA(-1)	-0.557099	0.078226	-7.121692	0.0000
RLX_TOTAL_SA(-2)	-0.280093	0.064102	-4.369463	0.0000
C	0.009078	0.003491	2.600657	0.0093
Variance Equation				
C(4)	-6.268455	0.129538	-48.39087	0.0000
C(5)	0.170076	0.165070	1.030329	0.3029
C(6)	0.178168	0.093174	1.912210	0.0558

R-squared	0.280095	Mean dependent var	0.004378
Adjusted R-squared	0.272354	S.D. dependent var	0.055522
S.E. of regression	0.047362	Akaike info criterion	-3.248089
Sum squared resid	0.417220	Schwarz criterion	-3.145177
Log likelihood	312.9444	Hannan-Quinn criter.	-3.206397
Durbin-Watson stat	2.116293		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 38 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_UK_SA(-1)	-0.307643	0.075766	-4.060435	0.0000
RLX_UK_SA(-2)	-0.228737	0.080206	-2.851886	0.0043
RLX_UK_SA(-3)	-0.195851	0.080031	-2.447200	0.0144
Variance Equation				
C(4)	-0.738357	0.461515	-1.599855	0.1096
C(5)	0.158654	0.092920	1.707418	0.0877
C(6)	-0.009262	0.050639	-0.182913	0.8549
C(7)	0.876197	0.090910	9.638063	0.0000

R-squared	0.092093	Mean dependent var	0.004140
Adjusted R-squared	0.082278	S.D. dependent var	0.088888
S.E. of regression	0.085153	Akaike info criterion	-2.053077
Sum squared resid	1.341428	Schwarz criterion	-1.932572
Log likelihood	199.9893	Hannan-Quinn criter.	-2.004253
Durbin-Watson stat	1.927093		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_BRAZIL_SA(-1)	-0.380837	0.066203	-5.752585	0.0000
ROP_BRAZIL_SA(-2)	-0.176884	0.061293	-2.885877	0.0039
Variance Equation				
C(3)	-1.730535	0.470768	-3.675981	0.0002
C(4)	0.174971	0.108490	1.612778	0.1068
C(5)	-0.356458	0.104318	-3.417035	0.0006
C(6)	0.562851	0.130304	4.319512	0.0000

R-squared	0.205891	Mean dependent var	0.010771
Adjusted R-squared	0.201644	S.D. dependent var	0.190909
S.E. of regression	0.170579	Akaike info criterion	-0.823693
Sum squared resid	5.441157	Schwarz criterion	-0.720780
Log likelihood	83.83900	Hannan-Quinn criter.	-0.782001
Durbin-Watson stat	2.306649		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M03 2016M12
Included observations: 190 after adjustments
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_FRANCE_SA(-1)	-0.385355	0.061872	-6.228222	0.0000
Variance Equation				
C(2)	-4.295226	0.122350	-35.10594	0.0000
C(3)	-0.138806	0.165982	-0.836270	0.4030
C(4)	-0.080609	0.124881	-0.645482	0.5186

R-squared	0.117585	Mean dependent var	0.009855
Adjusted R-squared	0.117585	S.D. dependent var	0.118339
S.E. of regression	0.111164	Akaike info criterion	-1.528218
Sum squared resid	2.335551	Schwarz criterion	-1.459860
Log likelihood	149.1807	Hannan-Quinn criter.	-1.500527
Durbin-Watson stat	2.010347		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_GERMANY_SA(-1)	-0.495709	0.094838	-5.226912	0.0000
ROP_GERMANY_SA(-2)	-0.289790	0.081780	-3.543517	0.0004
ROP_GERMANY_SA(-3)	-0.199296	0.064538	-3.088061	0.0020
ROP_GERMANY_SA(-4)	-0.208526	0.056005	-3.723324	0.0002
ROP_GERMANY_SA(-7)	0.165827	0.048292	3.433862	0.0006
Variance Equation				
C(6)	-4.563075	0.135194	-33.75206	0.0000
C(7)	0.746423	0.155359	4.804500	0.0000
C(8)	-0.046603	0.099620	-0.467811	0.6399

R-squared	0.336750	Mean dependent var	0.006919
Adjusted R-squared	0.321929	S.D. dependent var	0.172735
S.E. of regression	0.142239	Akaike info criterion	-1.103687
Sum squared resid	3.621492	Schwarz criterion	-0.963907
Log likelihood	109.5392	Hannan-Quinn criter.	-1.047033
Durbin-Watson stat	2.337243		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_ITALY_SA(-1)	-0.081884	0.047702	-1.716579	0.0861
ROP_ITALY_SA(-2)	-0.095695	0.060012	-1.594592	0.1108
ROP_ITALY_SA(-3)	-0.084418	0.060374	-1.398250	0.1620
Variance Equation				
C(4)	-5.623076	0.639735	-8.789694	0.0000
C(5)	0.695320	0.172172	4.038527	0.0001
C(6)	-0.379902	0.110455	-3.439435	0.0006
C(7)	-0.183116	0.158661	-1.154133	0.2484

R-squared	0.049788	Mean dependent var	0.005529
Adjusted R-squared	0.039515	S.D. dependent var	0.136510
S.E. of regression	0.133786	Akaike info criterion	-1.394027
Sum squared resid	3.311264	Schwarz criterion	-1.273521
Log likelihood	138.0385	Hannan-Quinn criter.	-1.345202
Durbin-Watson stat	2.399488		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_OTHERS_SA(-1)	-0.327982	0.076423	-4.291639	0.0000
ROP_OTHERS_SA(-2)	-0.198978	0.056320	-3.533007	0.0004
C	0.019119	0.006068	3.150839	0.0016
Variance Equation				
C(4)	-5.485041	0.149987	-36.57007	0.0000
C(5)	0.860567	0.121699	7.071281	0.0000
C(6)	0.184446	0.107717	1.712316	0.0868

R-squared	0.188605	Mean dependent var	0.008114
Adjusted R-squared	0.179880	S.D. dependent var	0.119027
S.E. of regression	0.107792	Akaike info criterion	-1.924041
Sum squared resid	2.161137	Schwarz criterion	-1.821128
Log likelihood	187.8218	Hannan-Quinn criter.	-1.882348
Durbin-Watson stat	2.403913		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(5) + C(6)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(7)
*RESID(-1)/@SQRT(GARCH(-1)) + C(8)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_PORTUGAL_SA(-1)	-0.622020	0.029149	-21.33954	0.0000
ROP_PORTUGAL_SA(-2)	-0.422987	0.043544	-9.714099	0.0000
ROP_PORTUGAL_SA(-3)	-0.217147	0.050847	-4.270566	0.0000
ROP_PORTUGAL_SA(-4)	-0.145941	0.053621	-2.721712	0.0065
Variance Equation				
C(5)	-0.522246	0.030065	-17.37038	0.0000
C(6)	-0.399714	0.040172	-9.949983	0.0000
C(7)	-0.067763	0.015464	-4.382135	0.0000
C(8)	0.853473	4.88E-05	17500.78	0.0000

R-squared	0.271227	Mean dependent var	0.002375
Adjusted R-squared	0.259280	S.D. dependent var	0.072657
S.E. of regression	0.062533	Akaike info criterion	-2.749378
Sum squared resid	0.715590	Schwarz criterion	-2.611149
Log likelihood	265.0668	Hannan-Quinn criter.	-2.693367
Durbin-Watson stat	1.979255		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_SPAIN_SA(-1)	-0.719927	0.048980	-14.69851	0.0000
ROP_SPAIN_SA(-2)	-0.458856	0.070261	-6.530757	0.0000
ROP_SPAIN_SA(-3)	-0.285288	0.059930	-4.760343	0.0000
ROP_SPAIN_SA(-4)	-0.131413	0.051650	-2.544285	0.0110
C	0.029197	0.009367	3.116833	0.0018
Variance Equation				
C(6)	-4.779467	0.130708	-36.56589	0.0000
C(7)	1.130483	0.124735	9.063084	0.0000
C(8)	0.224068	0.105934	2.115167	0.0344

R-squared	0.486739	Mean dependent var	0.008204
Adjusted R-squared	0.475459	S.D. dependent var	0.274288
S.E. of regression	0.198654	Akaike info criterion	-0.999875
Sum squared resid	7.182321	Schwarz criterion	-0.861646
Log likelihood	101.4883	Hannan-Quinn criter.	-0.943865
Durbin-Watson stat	2.587894		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_TOTAL_SA(-1)	-0.514334	0.084728	-6.070422	0.0000
ROP_TOTAL_SA(-2)	-0.170648	0.073075	-2.335223	0.0195
C	0.011487	0.004160	2.761240	0.0058
Variance Equation				
C(4)	-5.996793	0.123267	-48.64866	0.0000
C(5)	0.191934	0.179293	1.070505	0.2844
C(6)	0.126267	0.115617	1.092118	0.2748

R-squared	0.240503	Mean dependent var	0.005956
Adjusted R-squared	0.232337	S.D. dependent var	0.062289
S.E. of regression	0.054575	Akaike info criterion	-2.956246
Sum squared resid	0.553996	Schwarz criterion	-2.853333
Log likelihood	285.3652	Hannan-Quinn criter.	-2.914554
Durbin-Watson stat	2.089718		

Dependent Variable: ROP_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_UK_SA(-1)	-0.756120	0.043469	-17.39450	0.0000
ROP_UK_SA(-2)	-0.306995	0.077844	-3.943727	0.0001
ROP_UK_SA(-3)	-0.316023	0.087854	-3.597157	0.0003
ROP_UK_SA(-4)	-0.276194	0.073547	-3.755351	0.0002
ROP_UK_SA(-5)	-0.197518	0.073369	-2.692105	0.0071
Variance Equation				
C(6)	-6.850250	0.293669	-23.32643	0.0000
C(7)	-0.011683	0.077119	-0.151500	0.8796
C(8)	-0.253485	0.073588	-3.444666	0.0006
C(9)	-0.902281	0.047724	-18.90622	0.0000

R-squared	0.307595	Mean dependent var	0.007130
Adjusted R-squared	0.292293	S.D. dependent var	0.217634
S.E. of regression	0.183085	Akaike info criterion	-0.666743
Sum squared resid	6.067174	Schwarz criterion	-0.510659
Log likelihood	71.00713	Hannan-Quinn criter.	-0.603492
Durbin-Watson stat	1.863562		

Appendix J - EViews outputs for TGARCH models without lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.016155	0.015358	1.051887	0.2929
Variance Equation				
C	0.011930	0.004398	2.712654	0.0067
RESID(-1)^2	0.355764	0.162241	2.192818	0.0283
RESID(-1)^2*(RESID(-1)<0)	0.086164	0.279878	0.307864	0.7582
GARCH(-1)	0.417898	0.125757	3.323046	0.0009

R-squared	-0.000553	Mean dependent var	0.010582
Adjusted R-squared	-0.000553	S.D. dependent var	0.237659
S.E. of regression	0.237725	Akaike info criterion	-0.156230
Sum squared resid	10.73746	Schwarz criterion	-0.071092
Log likelihood	19.91992	Hannan-Quinn criter.	-0.121745
Durbin-Watson stat	2.717861		

Dependent Variable: RCB_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010005	0.014755	0.678085	0.4977
Variance Equation				
C	0.028377	0.003623	7.832253	0.0000
RESID(-1)^2	0.470459	0.305450	1.540218	0.1235
RESID(-1)^2*(RESID(-1)<0)	0.008091	0.362655	0.022310	0.9822

R-squared	-0.000957	Mean dependent var	0.002887
Adjusted R-squared	-0.000957	S.D. dependent var	0.230641
S.E. of regression	0.230752	Akaike info criterion	-0.232961
Sum squared resid	10.11682	Schwarz criterion	-0.164850
Log likelihood	26.24774	Hannan-Quinn criter.	-0.205373
Durbin-Watson stat	2.998241		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 27 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011290	0.015366	0.734759	0.4625
Variance Equation				
C	0.021307	0.004456	4.781720	0.0000
RESID(-1)^2	0.836792	0.358536	2.333913	0.0196
RESID(-1)^2*(RESID(-1)<0)	-0.612244	0.381059	-1.606688	0.1081
GARCH(-1)	0.196456	0.089876	2.185869	0.0288

R-squared	-0.002740	Mean dependent var	-0.000923
Adjusted R-squared	-0.002740	S.D. dependent var	0.233956
S.E. of regression	0.234276	Akaike info criterion	-0.169904
Sum squared resid	10.42823	Schwarz criterion	-0.084766
Log likelihood	21.22583	Hannan-Quinn criter.	-0.135419
Durbin-Watson stat	2.794513		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001956	0.016640	-0.117533	0.9064
Variance Equation				
C	0.043926	0.003981	11.03349	0.0000
RESID(-1)^2	0.300659	0.179514	1.674854	0.0940
RESID(-1)^2*(RESID(-1)<0)	-0.090386	0.247548	-0.365123	0.7150

R-squared	-0.000070	Mean dependent var	0.000119
Adjusted R-squared	-0.000070	S.D. dependent var	0.248254
S.E. of regression	0.248263	Akaike info criterion	-0.012311
Sum squared resid	11.71055	Schwarz criterion	0.055799
Log likelihood	5.175709	Hannan-Quinn criter.	0.015277
Durbin-Watson stat	2.980224		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015129	0.011204	1.350269	0.1769
Variance Equation				
C	0.018199	0.002055	8.854286	0.0000
RESID(-1)^2	0.521117	0.267071	1.951231	0.0510
RESID(-1)^2*(RESID(-1)<0)	-0.350703	0.289750	-1.210363	0.2261

R-squared	-0.004627	Mean dependent var	0.004136
Adjusted R-squared	-0.004627	S.D. dependent var	0.162017
S.E. of regression	0.162392	Akaike info criterion	-0.843667
Sum squared resid	5.010512	Schwarz criterion	-0.775557
Log likelihood	84.57021	Hannan-Quinn criter.	-0.816079
Durbin-Watson stat	2.595620		

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007273	0.005898	1.233253	0.2175
Variance Equation				
C	0.004623	0.000618	7.478667	0.0000
RESID(-1)^2	0.784576	0.314061	2.498167	0.0125
RESID(-1)^2*(RESID(-1)<0)	-0.444929	0.359483	-1.237692	0.2158

R-squared	-0.002610	Mean dependent var	0.002364
Adjusted R-squared	-0.002610	S.D. dependent var	0.096354
S.E. of regression	0.096479	Akaike info criterion	-1.987869
Sum squared resid	1.768569	Schwarz criterion	-1.919758
Log likelihood	193.8415	Hannan-Quinn criter.	-1.960281
Durbin-Watson stat	2.722965		

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.023325	0.015629	1.492451	0.1356
Variance Equation				
C	0.031917	0.003407	9.367125	0.0000
RESID(-1)^2	1.796706	0.449146	4.000271	0.0001
RESID(-1)^2*(RESID(-1)<0)	-1.602563	0.471353	-3.399923	0.0007

R-squared	-0.003986	Mean dependent var	0.001382
Adjusted R-squared	-0.003986	S.D. dependent var	0.348492
S.E. of regression	0.349186	Akaike info criterion	0.050838
Sum squared resid	23.16686	Schwarz criterion	0.118948
Log likelihood	-0.854991	Hannan-Quinn criter.	0.078425
Durbin-Watson stat	3.131428		

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002629	0.005852	0.449283	0.6532
Variance Equation				
C	0.004660	0.000580	8.037077	0.0000
RESID(-1)^2	0.463143	0.156514	2.959114	0.0031
RESID(-1)^2*(RESID(-1)<0)	-0.246324	0.244520	-1.007380	0.3138

R-squared	-0.000024	Mean dependent var	0.003045
Adjusted R-squared	-0.000024	S.D. dependent var	0.085637
S.E. of regression	0.085638	Akaike info criterion	-2.178973
Sum squared resid	1.393420	Schwarz criterion	-2.110862
Log likelihood	212.0919	Hannan-Quinn criter.	-2.151385
Durbin-Watson stat	2.684502		

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.003864	0.016570	-0.233192	0.8156
Variance Equation				
C	0.043906	0.005217	8.415679	0.0000
RESID(-1)^2	0.224529	0.154152	1.456541	0.1452
RESID(-1)^2*(RESID(-1)<0)	0.265127	0.270862	0.978830	0.3277

R-squared	-0.000702	Mean dependent var	0.003128
Adjusted R-squared	-0.000702	S.D. dependent var	0.264508
S.E. of regression	0.264601	Akaike info criterion	0.073378
Sum squared resid	13.30257	Schwarz criterion	0.141489
Log likelihood	-3.007632	Hannan-Quinn criter.	0.100966
Durbin-Watson stat	2.929510		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001220	0.008780	0.138923	0.8895
Variance Equation				
C	0.010813	0.000960	11.26463	0.0000
RESID(-1)^2	0.105662	0.085942	1.229463	0.2189
RESID(-1)^2*(RESID(-1)<0)	0.762640	0.338687	2.251754	0.0243

R-squared	-0.002822	Mean dependent var	0.008606
Adjusted R-squared	-0.002822	S.D. dependent var	0.139406
S.E. of regression	0.139603	Akaike info criterion	-1.330780
Sum squared resid	3.702890	Schwarz criterion	-1.262669
Log likelihood	131.0894	Hannan-Quinn criter.	-1.303192
Durbin-Watson stat	2.659834		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011070	0.006324	1.750556	0.0800
Variance Equation				
C	0.005219	0.000393	13.27816	0.0000
RESID(-1)^2	0.345476	0.117932	2.929440	0.0034
RESID(-1)^2*(RESID(-1)<0)	0.066621	0.229815	0.289889	0.7719

R-squared	-0.002720	Mean dependent var	0.006056
Adjusted R-squared	-0.002720	S.D. dependent var	0.096401
S.E. of regression	0.096532	Akaike info criterion	-2.026299
Sum squared resid	1.770487	Schwarz criterion	-1.958189
Log likelihood	197.5116	Hannan-Quinn criter.	-1.998711
Durbin-Watson stat	2.735099		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +
C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.014188	0.006806	2.084726	0.0371
Variance Equation				
C	0.002159	0.000887	2.433492	0.0150
RESID(-1)^2	0.604194	0.304718	1.982797	0.0474
RESID(-1)^2*(RESID(-1)<0)	-0.528445	0.308659	-1.712066	0.0869
GARCH(-1)	0.497195	0.127782	3.890975	0.0001

R-squared	-0.010001	Mean dependent var	0.004335
Adjusted R-squared	-0.010001	S.D. dependent var	0.098782
S.E. of regression	0.099275	Akaike info criterion	-1.870961
Sum squared resid	1.872556	Schwarz criterion	-1.785823
Log likelihood	183.6768	Hannan-Quinn criter.	-1.836477
Durbin-Watson stat	2.675628		

Dependent Variable: RLX_ITALY_SA
Method: ML - ARCH
Included observations: 191 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.005212	0.008258	0.631155	0.5279
Variance Equation				
C	0.009299	0.001456	6.386536	0.0000
RESID(-1)^2	0.345011	0.247683	1.392955	0.1636
RESID(-1)^2*(RESID(-1)<0)	0.044048	0.278911	0.157929	0.8745

R-squared	-0.000316	Mean dependent var	0.003112
Adjusted R-squared	-0.000316	S.D. dependent var	0.118493
S.E. of regression	0.118511	Akaike info criterion	-1.469943
Sum squared resid	2.668536	Schwarz criterion	-1.401833
Log likelihood	144.3796	Hannan-Quinn criter.	-1.442356
Durbin-Watson stat	2.798186		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011747	0.003699	3.175451	0.0015
Variance Equation				
C	0.002020	0.000260	7.773344	0.0000
RESID(-1)^2	1.068264	0.433181	2.466090	0.0137
RESID(-1)^2*(RESID(-1)<0)	-0.959234	0.435738	-2.201400	0.0277

R-squared	-0.008637	Mean dependent var	0.005851
Adjusted R-squared	-0.008637	S.D. dependent var	0.063615
S.E. of regression	0.063889	Akaike info criterion	-2.902689
Sum squared resid	0.775544	Schwarz criterion	-2.834579
Log likelihood	281.2068	Hannan-Quinn criter.	-2.875101
Durbin-Watson stat	2.589368		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002383	0.003216	0.741135	0.4586
	Variance Equation			
C	0.001539	0.000220	6.984212	0.0000
RESID(-1)^2	0.239919	0.141513	1.695385	0.0900
RESID(-1)^2*(RESID(-1)<0)	0.180556	0.247974	0.728126	0.4665

R-squared	-0.000001	Mean dependent var	0.002329
Adjusted R-squared	-0.000001	S.D. dependent var	0.047207
S.E. of regression	0.047207	Akaike info criterion	-3.296020
Sum squared resid	0.423415	Schwarz criterion	-3.227909
Log likelihood	318.7699	Hannan-Quinn criter.	-3.268432
Durbin-Watson stat	2.728028		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +
C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.018166	0.011427	1.589692	0.1119
	Variance Equation			
C	0.017682	0.001737	10.17941	0.0000
RESID(-1)^2	1.799366	0.446184	4.032786	0.0001
RESID(-1)^2*(RESID(-1)<0)	-1.576381	0.486951	-3.237245	0.0012
GARCH(-1)	-0.020132	0.008434	-2.387002	0.0170

R-squared	-0.004181	Mean dependent var	0.001967
Adjusted R-squared	-0.004181	S.D. dependent var	0.251155
S.E. of regression	0.251680	Akaike info criterion	-0.592860
Sum squared resid	12.03512	Schwarz criterion	-0.507722
Log likelihood	61.61813	Hannan-Quinn criter.	-0.558375
Durbin-Watson stat	3.258237		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007288	0.003757	1.939585	0.0524
	Variance Equation			
C	0.002187	0.000173	12.65284	0.0000
RESID(-1)^2	0.394943	0.191987	2.057132	0.0397
RESID(-1)^2*(RESID(-1)<0)	-0.284247	0.239904	-1.184833	0.2361

R-squared	-0.002635	Mean dependent var	0.004458
Adjusted R-squared	-0.002635	S.D. dependent var	0.055261
S.E. of regression	0.055334	Akaike info criterion	-3.040982
Sum squared resid	0.581755	Schwarz criterion	-2.972872
Log likelihood	294.4138	Hannan-Quinn criter.	-3.013394
Durbin-Watson stat	2.895293		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006916	0.006375	1.084893	0.2780
	Variance Equation			
C	0.006571	0.000715	9.194002	0.0000
RESID(-1)^2	0.300793	0.213222	1.410702	0.1583
RESID(-1)^2*(RESID(-1)<0)	-0.256878	0.222658	-1.153691	0.2486

R-squared	-0.001533	Mean dependent var	0.003437
Adjusted R-squared	-0.001533	S.D. dependent var	0.089113
S.E. of regression	0.089181	Akaike info criterion	-2.002713
Sum squared resid	1.511120	Schwarz criterion	-1.934603
Log likelihood	195.2591	Hannan-Quinn criter.	-1.975125
Durbin-Watson stat	2.457096		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002674	0.012929	-0.206838	0.8361
Variance Equation				
C	0.021211	0.001719	12.33685	0.0000
RESID(-1)^2	0.109387	0.075568	1.447534	0.1477
RESID(-1)^2*(RESID(-1)<0)	0.463287	0.291346	1.590164	0.1118

R-squared	-0.004765	Mean dependent var	0.010403
Adjusted R-squared	-0.004765	S.D. dependent var	0.189942
S.E. of regression	0.190394	Akaike info criterion	-0.717018
Sum squared resid	6.887486	Schwarz criterion	-0.648907
Log likelihood	72.47519	Hannan-Quinn criter.	-0.689430
Durbin-Watson stat	2.801031		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020992	0.010896	1.926581	0.0540
Variance Equation				
C	0.019763	0.003043	6.495115	0.0000
RESID(-1)^2	0.640437	0.246012	2.603279	0.0092
RESID(-1)^2*(RESID(-1)<0)	-0.243306	0.251353	-0.967984	0.3331
GARCH(-1)	-0.176032	0.088673	-1.985173	0.0471

R-squared	-0.005781	Mean dependent var	0.007650
Adjusted R-squared	-0.005781	S.D. dependent var	0.175940
S.E. of regression	0.176448	Akaike info criterion	-0.873267
Sum squared resid	5.915436	Schwarz criterion	-0.788129
Log likelihood	88.39704	Hannan-Quinn criter.	-0.838783
Durbin-Watson stat	2.973586		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.021748	0.006415	3.390376	0.0007
Variance Equation				
C	0.005320	0.000992	5.364073	0.0000
RESID(-1)^2	1.317296	0.427360	3.082404	0.0021
RESID(-1)^2*(RESID(-1)<0)	-1.093806	0.439707	-2.487580	0.0129

R-squared	-0.012451	Mean dependent var	0.008558
Adjusted R-squared	-0.012451	S.D. dependent var	0.118516
S.E. of regression	0.119251	Akaike info criterion	-1.798709
Sum squared resid	2.701964	Schwarz criterion	-1.730599
Log likelihood	175.7767	Hannan-Quinn criter.	-1.771121
Durbin-Watson stat	2.787427		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015543	0.008701	1.786439	0.0740
Variance Equation				
C	0.011066	0.001025	10.79292	0.0000
RESID(-1)^2	0.207911	0.150994	1.376944	0.1685
RESID(-1)^2*(RESID(-1)<0)	-0.013559	0.236842	-0.057249	0.9543

R-squared	-0.002817	Mean dependent var	0.009281
Adjusted R-squared	-0.002817	S.D. dependent var	0.118294
S.E. of regression	0.118460	Akaike info criterion	-1.439931
Sum squared resid	2.666246	Schwarz criterion	-1.371821
Log likelihood	141.5134	Hannan-Quinn criter.	-1.412343
Durbin-Watson stat	2.703350		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001350	0.007685	-0.175603	0.8606
Variance Equation				
C	0.009280	0.001286	7.216837	0.0000
RESID(-1)^2	0.053450	0.071310	0.749550	0.4535
RESID(-1)^2*(RESID(-1)<0)	1.371400	0.459709	2.983190	0.0029

R-squared	-0.001978	Mean dependent var	0.004683
Adjusted R-squared	-0.001978	S.D. dependent var	0.135994
S.E. of regression	0.136128	Akaike info criterion	-1.364721
Sum squared resid	3.520865	Schwarz criterion	-1.296611
Log likelihood	134.3309	Hannan-Quinn criter.	-1.337133
Durbin-Watson stat	2.444471		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004955	0.004499	1.101391	0.2707
Variance Equation				
C	0.004351	0.000583	7.467715	0.0000
RESID(-1)^2	0.504713	0.173329	2.911874	0.0036
RESID(-1)^2*(RESID(-1)<0)	-0.128217	0.173528	-0.738882	0.4600
GARCH(-1)	-0.214575	0.091347	-2.348993	0.0188

R-squared	-0.001230	Mean dependent var	0.002426
Adjusted R-squared	-0.001230	S.D. dependent var	0.072311
S.E. of regression	0.072355	Akaike info criterion	-2.490320
Sum squared resid	0.994707	Schwarz criterion	-2.405182
Log likelihood	242.8256	Hannan-Quinn criter.	-2.455835
Durbin-Watson stat	2.900189		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.023848	0.009680	2.463647	0.0138
	Variance Equation			
C	0.013268	0.002046	6.485544	0.0000
RESID(-1)^2	1.784656	0.407930	4.374911	0.0000
RESID(-1)^2*(RESID(-1)<0)	-1.186079	0.466375	-2.543189	0.0110

R-squared	-0.004021	Mean dependent var	0.006638
Adjusted R-squared	-0.004021	S.D. dependent var	0.272116
S.E. of regression	0.272663	Akaike info criterion	-0.553386
Sum squared resid	14.12557	Schwarz criterion	-0.485275
Log likelihood	56.84832	Hannan-Quinn criter.	-0.525798
Durbin-Watson stat	3.186206		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009913	0.004384	2.261311	0.0237
	Variance Equation			
C	0.002675	0.000257	10.38800	0.0000
RESID(-1)^2	0.566207	0.242776	2.332226	0.0197
RESID(-1)^2*(RESID(-1)<0)	-0.429327	0.270746	-1.585721	0.1128

R-squared	-0.003973	Mean dependent var	0.005988
Adjusted R-squared	-0.003973	S.D. dependent var	0.062429
S.E. of regression	0.062553	Akaike info criterion	-2.775766
Sum squared resid	0.743447	Schwarz criterion	-2.707656
Log likelihood	269.0857	Hannan-Quinn criter.	-2.748178
Durbin-Watson stat	2.912763		

Dependent Variable: ROP_UK_SA
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 2001M02 2016M12
Included observations: 191 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.033292	0.016699	1.993679	0.0462
	Variance Equation			
C	0.027003	0.002529	10.67753	0.0000
RESID(-1)^2	0.615292	0.544277	1.130475	0.2583
RESID(-1)^2*(RESID(-1)<0)	-0.311710	0.573983	-0.543065	0.5871

R-squared	-0.014585	Mean dependent var	0.006713
Adjusted R-squared	-0.014585	S.D. dependent var	0.220666
S.E. of regression	0.222269	Akaike info criterion	-0.358638
Sum squared resid	9.386678	Schwarz criterion	-0.290528
Log likelihood	38.24996	Hannan-Quinn criter.	-0.331050
Durbin-Watson stat	2.952121		

Appendix K - EViews outputs for TGARCH models with lags for Coimbra, Lisbon and Oporto

Dependent Variable: RCB_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_BRAZIL_SA(-1)	-0.483884	0.070118	-6.901007	0.0000
RCB_BRAZIL_SA(-2)	-0.239144	0.069790	-3.426628	0.0006
Variance Equation				
C	0.007790	0.003388	2.299487	0.0215
RESID(-1)^2	0.035240	0.059742	0.589875	0.5553
RESID(-1)^2*(RESID(-1)<0)	0.422254	0.175620	2.404353	0.0162
GARCH(-1)	0.630980	0.105892	5.958712	0.0000

R-squared	0.167608	Mean dependent var	0.009428
Adjusted R-squared	0.163156	S.D. dependent var	0.237340
S.E. of regression	0.217117	Akaike info criterion	-0.342826
Sum squared resid	8.815133	Schwarz criterion	-0.239913
Log likelihood	38.39703	Hannan-Quinn criter.	-0.301133
Durbin-Watson stat	1.956373		

Dependent Variable: RCB_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 42 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_FRANCE_SA(-1)	-0.808776	0.054334	-14.88516	0.0000
RCB_FRANCE_SA(-2)	-0.551139	0.089028	-6.190610	0.0000
RCB_FRANCE_SA(-3)	-0.404596	0.089671	-4.511989	0.0000
RCB_FRANCE_SA(-4)	-0.169898	0.079265	-2.143420	0.0321
Variance Equation				
C	0.030103	0.003551	8.477319	0.0000
RESID(-1)^2	-0.091583	0.040844	-2.242273	0.0249
RESID(-1)^2*(RESID(-1)<0)	0.541271	0.245420	2.205489	0.0274

R-squared	0.383783	Mean dependent var	0.002687
Adjusted R-squared	0.373681	S.D. dependent var	0.232561
S.E. of regression	0.184050	Akaike info criterion	-0.545917
Sum squared resid	6.199002	Schwarz criterion	-0.424967
Log likelihood	58.04327	Hannan-Quinn criter.	-0.496908
Durbin-Watson stat	1.961256		

Dependent Variable: RCB_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 22 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0) + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_GERMANY_SA(-1)	-0.684044	0.051503	-13.28174	0.0000
RCB_GERMANY_SA(-2)	-0.563242	0.065523	-8.596118	0.0000
RCB_GERMANY_SA(-3)	-0.382631	0.056568	-6.764064	0.0000
RCB_GERMANY_SA(-4)	-0.192749	0.062074	-3.105160	0.0019
Variance Equation				
C	0.073480	0.006933	10.59881	0.0000
RESID(-1)^2	-0.089418	0.025777	-3.468957	0.0005
RESID(-1)^2*(RESID(-1)<0)	0.108979	0.034389	3.169008	0.0015
GARCH(-1)	-0.868107	0.086052	-10.08816	0.0000

R-squared	0.298016	Mean dependent var	0.002013
Adjusted R-squared	0.286508	S.D. dependent var	0.233975
S.E. of regression	0.197635	Akaike info criterion	-0.375641
Sum squared resid	7.147925	Schwarz criterion	-0.237412
Log likelihood	43.12244	Hannan-Quinn criter.	-0.319630
Durbin-Watson stat	1.938369		

Dependent Variable: RCB_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_ITALY_SA(-1)	-0.821048	0.052997	-15.49231	0.0000
RCB_ITALY_SA(-2)	-0.534234	0.078842	-6.776004	0.0000
RCB_ITALY_SA(-3)	-0.323060	0.080105	-4.032976	0.0001
RCB_ITALY_SA(-4)	-0.130743	0.053092	-2.462562	0.0138
Variance Equation				
C	0.040023	0.003836	10.43484	0.0000
RESID(-1)^2	0.045642	0.191624	0.238184	0.8117
RESID(-1)^2*(RESID(-1)<0)	-0.109585	0.215794	-0.507825	0.6116

R-squared	0.342858	Mean dependent var	-0.000593
Adjusted R-squared	0.332085	S.D. dependent var	0.249447
S.E. of regression	0.203864	Akaike info criterion	-0.314559
Sum squared resid	7.605541	Schwarz criterion	-0.193608
Log likelihood	36.41122	Hannan-Quinn criter.	-0.265549
Durbin-Watson stat	1.838082		

Dependent Variable: RCB_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_OTHERS_SA(-1)	-0.387297	0.081950	-4.726009	0.0000
RCB_OTHERS_SA(-2)	-0.342228	0.077736	-4.402449	0.0000
RCB_OTHERS_SA(-3)	-0.162525	0.077297	-2.102620	0.0355
RCB_OTHERS_SA(-5)	-0.145718	0.060235	-2.419149	0.0156
		Variance Equation		
C	0.018371	0.001890	9.718941	0.0000
RESID(-1)^2	0.146906	0.139685	1.051701	0.2929
RESID(-1)^2*(RESID(-1)<0)	-0.031730	0.167408	-0.189535	0.8497
R-squared	0.204874	Mean dependent var		0.004022
Adjusted R-squared	0.191767	S.D. dependent var		0.163711
S.E. of regression	0.147179	Akaike info criterion		-0.960258
Sum squared resid	3.942424	Schwarz criterion		-0.838859
Log likelihood	96.30401	Hannan-Quinn criter.		-0.911063
Durbin-Watson stat	2.198341			

Dependent Variable: RCB_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 11 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_PORTUGAL_SA(-1)	-0.439424	0.047505	-9.250054	0.0000
RCB_PORTUGAL_SA(-2)	-0.317363	0.056591	-5.608006	0.0000
RCB_PORTUGAL_SA(-3)	-0.112633	0.068752	-1.638260	0.1014
RCB_PORTUGAL_SA(-4)	-0.288899	0.057553	-5.019695	0.0000
		Variance Equation		
C	0.005371	0.000746	7.203263	0.0000
RESID(-1)^2	0.522924	0.259453	2.015484	0.0439
RESID(-1)^2*(RESID(-1)<0)	-0.598858	0.246750	-2.426980	0.0152
R-squared	0.259154	Mean dependent var		0.002761
Adjusted R-squared	0.247009	S.D. dependent var		0.097089
S.E. of regression	0.084249	Akaike info criterion		-2.183554
Sum squared resid	1.298906	Schwarz criterion		-2.062604
Log likelihood	211.1623	Hannan-Quinn criter.		-2.134545
Durbin-Watson stat	2.095892			

Dependent Variable: RCB_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 22 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*RESID(-1)^2*(RESID(-1)<0) + C(11)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_SPAIN_SA(-1)	-0.945060	0.096715	-9.771560	0.0000
RCB_SPAIN_SA(-2)	-0.848189	0.107402	-7.897338	0.0000
RCB_SPAIN_SA(-3)	-0.658111	0.116141	-5.666479	0.0000
RCB_SPAIN_SA(-4)	-0.439682	0.143577	-3.062334	0.0022
RCB_SPAIN_SA(-5)	-0.380190	0.139456	-2.726240	0.0064
RCB_SPAIN_SA(-6)	-0.285863	0.129562	-2.206376	0.0274
RCB_SPAIN_SA(-7)	-0.145897	0.081019	-1.800778	0.0717
		Variance Equation		
C	0.019032	0.011270	1.688759	0.0913
RESID(-1)^2	0.150312	0.069391	2.166157	0.0303
RESID(-1)^2*(RESID(-1)<0)	-0.238417	0.083401	-2.858680	0.0043
GARCH(-1)	0.569139	0.263354	2.161112	0.0307
R-squared	0.540823	Mean dependent var		0.001825
Adjusted R-squared	0.525257	S.D. dependent var		0.354168
S.E. of regression	0.244028	Akaike info criterion		-0.117392
Sum squared resid	10.54026	Schwarz criterion		0.074805
Log likelihood	21.80006	Hannan-Quinn criter.		-0.039492
Durbin-Watson stat	2.262146			

Dependent Variable: RCB_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_TOTAL_SA(-1)	-0.499263	0.069145	-7.220546	0.0000
RCB_TOTAL_SA(-2)	-0.333893	0.057657	-5.791040	0.0000
		Variance Equation		
C	0.003488	0.000505	6.903492	0.0000
RESID(-1)^2	0.739825	0.241353	3.065318	0.0022
RESID(-1)^2*(RESID(-1)<0)	-0.606035	0.258898	-2.340825	0.0192
R-squared	0.227443	Mean dependent var		0.003022
Adjusted R-squared	0.223311	S.D. dependent var		0.086075
S.E. of regression	0.075858	Akaike info criterion		-2.396958
Sum squared resid	1.076084	Schwarz criterion		-2.311197
Log likelihood	231.5125	Hannan-Quinn criter.		-2.362214
Durbin-Watson stat	1.956582			

Dependent Variable: RCB_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2 + C(9)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RCB_UK_SA(-1)	-0.596573	0.088192	-6.764510	0.0000
RCB_UK_SA(-2)	-0.281319	0.076691	-3.668197	0.0002
RCB_UK_SA(-3)	-0.312311	0.077498	-4.029918	0.0001
RCB_UK_SA(-4)	-0.194844	0.080641	-2.416180	0.0157
RCB_UK_SA(-5)	-0.154153	0.077923	-1.978272	0.0479
RCB_UK_SA(-6)	-0.170332	0.073248	-2.325402	0.0201
Variance Equation				
C	0.033512	0.004688	7.147946	0.0000
RESID(-1)^2	0.192957	0.128506	1.501541	0.1332
RESID(-1)^2*(RESID(-1)<0)	0.231405	0.221859	1.043026	0.2969

R-squared	0.316584	Mean dependent var	0.001506
Adjusted R-squared	0.297494	S.D. dependent var	0.265361
S.E. of regression	0.222414	Akaike info criterion	-0.184491
Sum squared resid	8.854773	Schwarz criterion	-0.027825
Log likelihood	26.06544	Hannan-Quinn criter.	-0.120998
Durbin-Watson stat	2.047836		

Dependent Variable: RLX_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_BRAZIL_SA(-1)	-0.342263	0.069844	-4.900394	0.0000
RLX_BRAZIL_SA(-2)	-0.173053	0.077795	-2.224476	0.0261
Variance Equation				
C	0.004903	0.001713	2.862442	0.0042
RESID(-1)^2	-0.057164	0.004931	-11.59240	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.394704	0.127849	3.087277	0.0020
GARCH(-1)	0.539959	0.157390	3.430709	0.0006

R-squared	0.152803	Mean dependent var	0.007812
Adjusted R-squared	0.148272	S.D. dependent var	0.139894
S.E. of regression	0.129107	Akaike info criterion	-1.417506
Sum squared resid	3.117024	Schwarz criterion	-1.314593
Log likelihood	139.9543	Hannan-Quinn criter.	-1.375814
Durbin-Watson stat	2.159650		

Dependent Variable: RLX_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_FRANCE_SA(-1)	-0.504793	0.092270	-5.470804	0.0000
RLX_FRANCE_SA(-2)	-0.165954	0.060391	-2.748006	0.0060
C	0.013939	0.006284	2.218201	0.0265
Variance Equation				
C	0.005506	0.000405	13.59171	0.0000
RESID(-1)^2	0.052864	0.100156	0.527821	0.5976
RESID(-1)^2*(RESID(-1)<0)	0.066858	0.178875	0.373771	0.7086

R-squared	0.247880	Mean dependent var	0.007824
Adjusted R-squared	0.239792	S.D. dependent var	0.089919
S.E. of regression	0.078400	Akaike info criterion	-2.222280
Sum squared resid	1.143265	Schwarz criterion	-2.119367
Log likelihood	216.0054	Hannan-Quinn criter.	-2.180588
Durbin-Watson stat	2.121495		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_GERMANY_SA(-1)	-0.461861	0.076772	-6.016021	0.0000
RLX_GERMANY_SA(-2)	-0.278007	0.072596	-3.829520	0.0001
RLX_GERMANY_SA(-3)	-0.204471	0.070222	-2.911805	0.0036
RLX_GERMANY_SA(-4)	-0.152311	0.065134	-2.338428	0.0194
Variance Equation				
C	0.006110	0.000938	6.515871	0.0000
RESID(-1)^2	0.205871	0.170316	1.208756	0.2268
RESID(-1)^2*(RESID(-1)<0)	0.001213	0.199415	0.006085	0.9951

R-squared	0.194231	Mean dependent var	0.004713
Adjusted R-squared	0.181022	S.D. dependent var	0.097687
S.E. of regression	0.088404	Akaike info criterion	-1.989523
Sum squared resid	1.430206	Schwarz criterion	-1.868573
Log likelihood	193.0204	Hannan-Quinn criter.	-1.940514
Durbin-Watson stat	2.060992		

Dependent Variable: RLX_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M06 2016M12
Included observations: 187 after adjustments
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_GERMANY_SA(-1)	-0.461861	0.076772	-6.016021	0.0000
RLX_GERMANY_SA(-2)	-0.278007	0.072596	-3.829520	0.0001
RLX_GERMANY_SA(-3)	-0.204471	0.070222	-2.911805	0.0036
RLX_GERMANY_SA(-4)	-0.152311	0.065134	-2.338428	0.0194
	Variance Equation			
C	0.006110	0.000938	6.515871	0.0000
RESID(-1)^2	0.205871	0.170316	1.208756	0.2268
RESID(-1)^2*(RESID(-1)<0)	0.001213	0.199415	0.006085	0.9951

R-squared	0.194231	Mean dependent var	0.004713
Adjusted R-squared	0.181022	S.D. dependent var	0.097687
S.E. of regression	0.088404	Akaike info criterion	-1.989523
Sum squared resid	1.430206	Schwarz criterion	-1.868573
Log likelihood	193.0204	Hannan-Quinn criter.	-1.940514
Durbin-Watson stat	2.060992		

Dependent Variable: RLX_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_OTHERS_SA(-1)	-0.205047	0.074295	-2.759895	0.0058
RLX_OTHERS_SA(-2)	-0.120421	0.057264	-2.102927	0.0355
C	0.009952	0.003574	2.784219	0.0054
	Variance Equation			
C	0.001860	0.000239	7.788973	0.0000
RESID(-1)^2	1.109567	0.362694	3.059235	0.0022
RESID(-1)^2*(RESID(-1)<0)	-0.987195	0.351857	-2.805671	0.0050

R-squared	0.126910	Mean dependent var	0.005527
Adjusted R-squared	0.117522	S.D. dependent var	0.063422
S.E. of regression	0.059579	Akaike info criterion	-2.955547
Sum squared resid	0.660241	Schwarz criterion	-2.852634
Log likelihood	285.2992	Hannan-Quinn criter.	-2.913855
Durbin-Watson stat	2.301577		

Dependent Variable: RLX_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_PORTUGAL_SA(-1)	-0.413811	0.077962	-5.307870	0.0000
RLX_PORTUGAL_SA(-2)	-0.197999	0.071841	-2.756076	0.0058
	Variance Equation			
C	0.001552	0.000218	7.121075	0.0000
RESID(-1)^2	0.063319	0.089084	0.710781	0.4772
RESID(-1)^2*(RESID(-1)<0)	0.278700	0.212027	1.314460	0.1887

R-squared	0.157085	Mean dependent var	0.002269
Adjusted R-squared	0.152578	S.D. dependent var	0.047454
S.E. of regression	0.043684	Akaike info criterion	-3.415071
Sum squared resid	0.356847	Schwarz criterion	-3.329311
Log likelihood	327.7242	Hannan-Quinn criter.	-3.380328
Durbin-Watson stat	2.068285		

Dependent Variable: RLX_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M07 2016M12
Included observations: 186 after adjustments
Convergence achieved after 18 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*RESID(-1)^2*(RESID(-1)<0) +
C(9)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_SPAIN_SA(-1)	-0.923604	0.056619	-16.31271	0.0000
RLX_SPAIN_SA(-2)	-0.683174	0.069534	-9.825081	0.0000
RLX_SPAIN_SA(-3)	-0.484356	0.067702	-7.154185	0.0000
RLX_SPAIN_SA(-4)	-0.293482	0.071467	-4.106545	0.0000
RLX_SPAIN_SA(-5)	-0.167174	0.057282	-2.918460	0.0035
	Variance Equation			
C	0.002539	0.000767	3.310798	0.0009
RESID(-1)^2	0.223325	0.047382	4.713293	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.296225	0.052849	-5.605100	0.0000
GARCH(-1)	0.798093	0.048665	16.39975	0.0000

R-squared	0.553523	Mean dependent var	0.001713
Adjusted R-squared	0.543656	S.D. dependent var	0.253937
S.E. of regression	0.171543	Akaike info criterion	-0.999748
Sum squared resid	5.326288	Schwarz criterion	-0.843664
Log likelihood	101.9766	Hannan-Quinn criter.	-0.936497
Durbin-Watson stat	2.298813		

Dependent Variable: RLX_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0) + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_TOTAL_SA(-1)	-0.554950	0.073130	-7.588564	0.0000
RLX_TOTAL_SA(-2)	-0.310124	0.092028	-3.369882	0.0008
RLX_TOTAL_SA(-3)	-0.060488	0.090736	-0.666635	0.5050
C	0.011006	0.003342	3.293694	0.0010
Variance Equation				
C	4.05E-05	1.64E-05	2.478587	0.0132
RESID(-1)^2	-0.001211	0.022474	-0.053872	0.9570
RESID(-1)^2*(RESID(-1)<0)	-0.085420	0.032506	-2.627814	0.0086
GARCH(-1)	1.018407	0.000236	4308.415	0.0000

R-squared	0.282727	Mean dependent var	0.004629
Adjusted R-squared	0.271033	S.D. dependent var	0.055562
S.E. of regression	0.047439	Akaike info criterion	-3.334081
Sum squared resid	0.414084	Schwarz criterion	-3.196360
Log likelihood	321.4036	Hannan-Quinn criter.	-3.278282
Durbin-Watson stat	2.108889		

Dependent Variable: RLX_UK_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RLX_UK_SA(-1)	-0.252398	0.085404	-2.955363	0.0031
RLX_UK_SA(-2)	-0.171286	0.072786	-2.353295	0.0186
RLX_UK_SA(-3)	-0.170763	0.074036	-2.306492	0.0211
Variance Equation				
C	0.006777	0.000730	9.279715	0.0000
RESID(-1)^2	0.106170	0.163349	0.649956	0.5157
RESID(-1)^2*(RESID(-1)<0)	-0.139547	0.175309	-0.796008	0.4260

R-squared	0.093899	Mean dependent var	0.004140
Adjusted R-squared	0.084104	S.D. dependent var	0.088888
S.E. of regression	0.085068	Akaike info criterion	-2.055062
Sum squared resid	1.338759	Schwarz criterion	-1.951771
Log likelihood	199.1758	Hannan-Quinn criter.	-2.013212
Durbin-Watson stat	2.041890		

Dependent Variable: ROP_BRAZIL_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_BRAZIL_SA(-1)	-0.473229	0.056677	-8.349524	0.0000
ROP_BRAZIL_SA(-2)	-0.272748	0.084958	-3.210382	0.0013
ROP_BRAZIL_SA(-3)	-0.128722	0.063732	-2.019734	0.0434
Variance Equation				
C	0.011635	0.003151	3.692701	0.0002
RESID(-1)^2	-0.153154	0.044474	-3.443662	0.0006
RESID(-1)^2*(RESID(-1)<0)	0.565859	0.227676	2.485366	0.0129
GARCH(-1)	0.467645	0.134349	3.480826	0.0005

R-squared	0.232312	Mean dependent var	0.010343
Adjusted R-squared	0.224013	S.D. dependent var	0.191328
S.E. of regression	0.168541	Akaike info criterion	-0.841836
Sum squared resid	5.255137	Schwarz criterion	-0.721330
Log likelihood	86.13256	Hannan-Quinn criter.	-0.793011
Durbin-Watson stat	2.175128		

Dependent Variable: ROP_FRANCE_SA
Method: ML - ARCH
Sample (adjusted): 2001M03 2016M12
Included observations: 190 after adjustments
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_FRANCE_SA(-1)	-0.375321	0.068786	-5.456328	0.0000
Variance Equation				
C	0.012629	0.001091	11.58030	0.0000
RESID(-1)^2	-0.029717	0.069745	-0.426087	0.6700
RESID(-1)^2*(RESID(-1)<0)	0.003716	0.133668	0.027800	0.9778

R-squared	0.118128	Mean dependent var	0.009855
Adjusted R-squared	0.118128	S.D. dependent var	0.118339
S.E. of regression	0.111130	Akaike info criterion	-1.521658
Sum squared resid	2.334113	Schwarz criterion	-1.453299
Log likelihood	148.5575	Hannan-Quinn criter.	-1.493967
Durbin-Watson stat	2.027875		

Dependent Variable: ROP_GERMANY_SA
Method: ML - ARCH
Sample (adjusted): 2001M09 2016M12
Included observations: 184 after adjustments
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(7) + C(8)*RESID(-1)^2 + C(9)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_GERMANY_SA(-1)	-0.599257	0.093625	-6.400580	0.0000
ROP_GERMANY_SA(-2)	-0.352395	0.110757	-3.181682	0.0015
ROP_GERMANY_SA(-3)	-0.277162	0.091556	-3.027233	0.0025
ROP_GERMANY_SA(-4)	-0.272499	0.079001	-3.449337	0.0006
ROP_GERMANY_SA(-5)	-0.156427	0.071715	-2.181232	0.0292
ROP_GERMANY_SA(-7)	0.142437	0.056693	2.512435	0.0120
Variance Equation				
C	0.014579	0.001527	9.548241	0.0000
RESID(-1)^2	0.224959	0.114451	1.965554	0.0494
RESID(-1)^2*(RESID(-1)<0)	0.095281	0.187734	0.507533	0.6118

R-squared	0.364704	Mean dependent var	0.006919
Adjusted R-squared	0.346859	S.D. dependent var	0.172735
S.E. of regression	0.139599	Akaike info criterion	-1.079372
Sum squared resid	3.468856	Schwarz criterion	-0.922119
Log likelihood	108.3022	Hannan-Quinn criter.	-1.015635
Durbin-Watson stat	2.129918		

Dependent Variable: ROP_ITALY_SA
Method: ML - ARCH
Sample (adjusted): 2001M08 2016M12
Included observations: 185 after adjustments
Convergence achieved after 36 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_ITALY_SA(-1)	-0.124937	0.060478	-2.065816	0.0388
ROP_ITALY_SA(-2)	-0.142410	0.070975	-2.006488	0.0448
ROP_ITALY_SA(-3)	-0.139902	0.066031	-2.118728	0.0341
ROP_ITALY_SA(-4)	-0.130740	0.079005	-1.654840	0.0980
ROP_ITALY_SA(-6)	-0.101735	0.047991	-2.119861	0.0340
Variance Equation				
C	0.009094	0.001253	7.259016	0.0000
RESID(-1)^2	0.041436	0.065363	0.633949	0.5261
RESID(-1)^2*(RESID(-1)<0)	1.288129	0.424327	3.035698	0.0024

R-squared	0.101953	Mean dependent var	0.005629
Adjusted R-squared	0.081996	S.D. dependent var	0.137086
S.E. of regression	0.131346	Akaike info criterion	-1.386897
Sum squared resid	3.105297	Schwarz criterion	-1.247638
Log likelihood	136.2879	Hannan-Quinn criter.	-1.330458
Durbin-Watson stat	2.353416		

Dependent Variable: ROP_OTHERS_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_OTHERS_SA(-1)	-0.436625	0.089371	-4.885511	0.0000
ROP_OTHERS_SA(-2)	-0.210717	0.065656	-3.209417	0.0013
C	0.021636	0.006472	3.342961	0.0008
Variance Equation				
C	0.005626	0.000808	6.959714	0.0000
RESID(-1)^2	0.864753	0.217516	3.975578	0.0001
RESID(-1)^2*(RESID(-1)<0)	-0.686606	0.244518	-2.807997	0.0050

R-squared	0.211520	Mean dependent var	0.008114
Adjusted R-squared	0.203042	S.D. dependent var	0.119027
S.E. of regression	0.106259	Akaike info criterion	-1.897040
Sum squared resid	2.100103	Schwarz criterion	-1.794127
Log likelihood	185.2702	Hannan-Quinn criter.	-1.855347
Durbin-Watson stat	2.183424		

Dependent Variable: ROP_PORTUGAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) +
C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_PORTUGAL_SA(-1)	-0.499616	0.055504	-9.001427	0.0000
ROP_PORTUGAL_SA(-2)	-0.190120	0.064945	-2.927374	0.0034
Variance Equation				
C	0.000342	5.29E-05	6.473011	0.0000
RESID(-1)^2	-0.054812	0.009716	-5.641181	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.059585	0.034173	-1.743619	0.0812
GARCH(-1)	0.997425	0.013631	73.17192	0.0000

R-squared	0.250410	Mean dependent var	0.002378
Adjusted R-squared	0.246401	S.D. dependent var	0.072276
S.E. of regression	0.062743	Akaike info criterion	-2.735283
Sum squared resid	0.736151	Schwarz criterion	-2.632371
Log likelihood	264.4843	Hannan-Quinn criter.	-2.693591
Durbin-Watson stat	2.170001		

Dependent Variable: ROP_SPAIN_SA
Method: ML - ARCH
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 58 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_SPAIN_SA(-1)	-0.684705	0.071017	-9.641473	0.0000
ROP_SPAIN_SA(-2)	-0.357952	0.070123	-5.104643	0.0000
ROP_SPAIN_SA(-3)	-0.152113	0.053678	-2.833828	0.0046
C	0.027988	0.009786	2.860014	0.0042
		Variance Equation		
C	0.011084	0.001433	7.735625	0.0000
RESID(-1)^2	1.335929	0.383681	3.481875	0.0005
RESID(-1)^2*(RESID(-1)<0)	-0.856142	0.402762	-2.125680	0.0335

R-squared	0.472552	Mean dependent var	0.006933
Adjusted R-squared	0.463952	S.D. dependent var	0.274109
S.E. of regression	0.200689	Akaike info criterion	-0.902803
Sum squared resid	7.410825	Schwarz criterion	-0.782297
Log likelihood	91.86349	Hannan-Quinn criter.	-0.853979
Durbin-Watson stat	2.556887		

Dependent Variable: ROP_TOTAL_SA
Method: ML - ARCH
Sample (adjusted): 2001M04 2016M12
Included observations: 189 after adjustments
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_TOTAL_SA(-1)	-0.511789	0.083096	-6.159004	0.0000
ROP_TOTAL_SA(-2)	-0.161205	0.074832	-2.154234	0.0312
C	0.011368	0.004117	2.761047	0.0058
		Variance Equation		
C	0.002537	0.000236	10.75556	0.0000
RESID(-1)^2	0.263124	0.175223	1.501651	0.1332
RESID(-1)^2*(RESID(-1)<0)	-0.235658	0.190661	-1.236010	0.2165

R-squared	0.240348	Mean dependent var	0.005956
Adjusted R-squared	0.232180	S.D. dependent var	0.062289
S.E. of regression	0.054581	Akaike info criterion	-2.961432
Sum squared resid	0.554109	Schwarz criterion	-2.858519
Log likelihood	285.8553	Hannan-Quinn criter.	-2.919739
Durbin-Watson stat	2.092993		

Dependent Variable: ROP_UK_SA
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 2001M05 2016M12
Included observations: 188 after adjustments
Convergence achieved after 43 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROP_UK_SA(-1)	-0.554064	0.079826	-6.940866	0.0000
ROP_UK_SA(-2)	-0.209767	0.073615	-2.849501	0.0044
ROP_UK_SA(-3)	-0.141578	0.059803	-2.367385	0.0179
		Variance Equation		
C	0.000427	0.000573	0.745729	0.4558
RESID(-1)^2	0.031319	0.020551	1.523953	0.1275
RESID(-1)^2*(RESID(-1)<0)	0.059274	0.064421	0.920097	0.3575
GARCH(-1)	0.931806	0.029708	31.36600	0.0000

R-squared	0.291806	Mean dependent var	0.007461
Adjusted R-squared	0.284150	S.D. dependent var	0.216567
S.E. of regression	0.183233	Akaike info criterion	-0.577501
Sum squared resid	6.211257	Schwarz criterion	-0.456995
Log likelihood	61.28508	Hannan-Quinn criter.	-0.528676
Durbin-Watson stat	2.165863		