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Tourism, terrorism and political violence in Tunisia: Evidence from Markov-switching models

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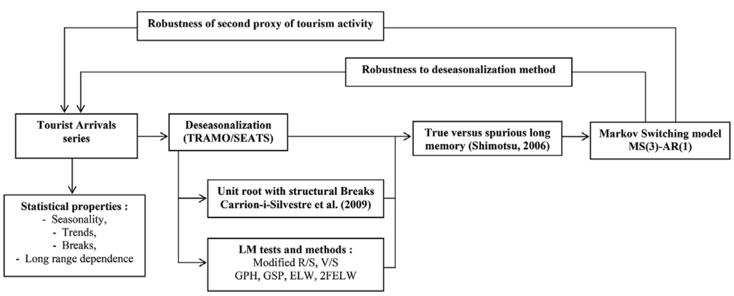
GRAPHICAL ABSTRACT



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ABSTRACT

This study investigates the impact of terrorist attacks and political violence on the number of tourist arrivals and overnight stays in Tunisia. The dataset employed consists of monthly data that covers the period from January 2000 to September 2016, which includes several political and terrorist attacks in Tunisia and the region. Empirically, we investigate the true data generating process (DGP) of these two proxies of tourism activity by accounting for four statistical properties that characterize these series: (1) seasonality, (2) unit roots, (3) breaks, and (4) long memory behavior.

Our empirical findings show strong evidence of stationarity, five breaks in the tourist arrival time series and spurious long memory behavior. By estimating a 3-state Markov switching model consisting of the mean, trend, and variance, we find that the Tunisian Jasmine revolution and two recent terrorist attacks, one at the Bardo National Museum on March 18, 2015 and the other at the tourist resort at Port El Kantaoui, Sousse on June 26, 2015, played an important role in influencing the tourism activity of the country. Our empirical findings show also that local shocks have a more important impact than international shocks in influencing tourism activity. Interestingly, we find that the effects of terrorist shocks have a long duration compared to political violence shocks. Several security, marketing, and economic policies have been proposed and discussed in the paper.

1. Introduction

Throughout the world, tourism has become one of the industries most exposed to political unrest and terrorist attacks (Arana & Leon, 2008; Causevic & Lynch, 2013; Peter et al., 2014; Wolff & Larsen, 2014; and; Avraham, 2016). In particular, since the beginning of the century, many democracies from developed countries have exhibited high levels of terrorist episodes. Starting with the September 11 Twin Towers attack in New York City in 2001, followed by the bombing events in Madrid in 2004 and London in 2005, and ending with the terrorist

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attacks in Brussels, Paris, and Berlin in 2016, terrorist incidents have created deep economic concern for the tourism industry. Recently, following the Arab Spring, an unprecedented wave of political violence and terrorist events have occurred in several MENA tourism-dependent economies, keeping tourists away from Egypt, Tunisia, and Turkey.

An important issue when proposing economic policies or designing a complete tourism strategy to restore tourism activity following political violence or terrorist attacks is the exact determination of the path time of these shocks. Indeed, the tourism industry is a sensitive sector and closely connected to other sectors (transport, trade, information and communications technology), so the social cost of such shocks can be damaging in terms of job losses and social exclusion if the recovery takes time. Therefore, the necessity to measure the time length of each shock is pertinent for policymakers and managers in the tourism industry. Furthermore, studies show that recovery is likely to be slow, as repeated incidents of violence tend to have long-lasting effects on tourist arrivals (IMF, 2017). To this end, it is important to determine whether these shocks have a transitory, persistent, or permanent impact. Estrada and Koutronas (2016) argue that “such severe shocks, concentrated in time, can cause major disruption on specific sectors of the economy.” Based on these reports, it is important to focus on these shocks and study if political violence or terrorist attacks are transitory or persistent shocks, which will help to determine which type of policies should be recommended and implemented to recover from their negative effects.

Our choice of Tunisia as a case study of the impact of political violence and terrorist attacks on tourism activity is motivated by the growing place and important role that the tourism sector has in the Tunisian economy. Tunisia is a tourism-dependent economy, and the industry is considered one of the main drivers of the country's economic growth. For many years, the tourism sector has contributed to more than 7% of Tunisia's real GDP. In addition, this sector is one of the main sources of its foreign exchange. Furthermore, the tourism industry represents an important source of job creation, creating more than 400,000 jobs. Despite the importance of the tourism industry in the Tunisian economy, few studies have researched tourism in Tunisia. (see for instance Ouerfelli, 2008; Gasmi & Sassi, 2015; Jlassi, Fliti, & Chaibi, 2015; and Ben Aissa and Goaied, 2016).

The present study adds to the international tourism demand literature by examining and determining the true nature of the data-generating process (DGP) of two tourism activity proxies for the case of Tunisia (the number of tourist arrivals and the number of overnight stays). To this end, this paper explores several possible DGPs to model these two series. These alternatives include short memory models with breaks, processes characterized by unit roots, and models characterized by long-range dependence. Moreover, given the importance of the effective timing of tourism action, which can be drawn from modeling and determining the true DGP of the monthly time series, we investigate the short-run impact and the duration effects of two particular shocks in Tunisia: terrorist attacks and political violence shocks. To the best of our knowledge, this is the first study that attempts to examine the effects of those types of shocks on tourism activity using Tunisian data, recent econometric developments based on long-range dependence, and Markov switching models, as well as how to differentiate between these two processes.

The rest of this paper is organized as follows. Section 2 presents an overview of the literature review on terrorism and international tourism demand. Section 3 outlines the tourism sector in Tunisia and the different shocks that affect the series of the monthly number of tourist arrivals and nights. Section 4 presents the empirical methodology followed throughout the paper. Section 5 investigates the true DGP of the series of the number of tourist arrivals using several models. Section 6 uses Markov switching models with changes in the intercept, trend, and variance to model tourist arrivals and assess the robustness of our results to a second proxy of the tourism activity and a second technique of deseasonalization. Section 7 concludes the paper and highlights the main policy implications.

2. Literature review

Terrorism and political violence have grown into a primary consideration for the tourism industry because these incidents seem to affect tourism activity more severely than all other types of shocks, such as natural catastrophes, financial crises, or health crises (Sonmez, 1998). Neumayear (2004) and Reisenger and Mavondo (2005) highlight the handicap effect of terrorism and political turmoil on the development of new destinations because consumer decisions show a preference for regions with more political stability and characterized by a peaceful social environment. Arana and Leon (2008) underlined the precarity of tourism following turbulences; both demand and supply can be sensitive to extreme events, such as terrorism or political violence. The empirical literature focusing on the impact of events (political violence, terrorist attacks, etc.) on international tourism demand can be classified into two groups.

2.1. Transitory or permanent shock on tourism demand

The first strand is based on determining whether the impact of such shocks on the tourism demand is transitory or permanent. Barros, Gil-Alana, and Wanke (2016) highlight that “a shock is known to have a temporary or short term effect if after a few number of periods the series return backs to its original performance level.” For example, the impact of political violence and/or a terrorist attack shocks on the number of tourist arrivals vanishes quickly (after a few observations) and the demand recovers its primary realization. In contrast, there is evidence of a persistent or long-term impact, if the short-run effect of shocks converges toward a new trend in the achievement of demand.

Researchers have explored this possibility by applying unit root tests to tourism activity proxies (see Narayan, 2005, 2008; Lean & Smyth, 2009 among many others). For instance, using several unit root tests with structural breaks, Narayan (2005) shows that the 1987 political coups in Fiji had only transitory effects on tourist arrivals and tourist expenditures. Narayan (2008) investigates, in the context of panel data, the effect of shocks to international tourist arrivals in the case of Australia and shows these shocks have only a transitory impact. Lean and Smyth (2009) investigated the impact of shocks to international visitor arrivals from Malaysia's 10 major source markets. Using Lagrange Multiplier (LM) unit root tests with one and two structural breaks, the authors found evidence for stationarity of the tourist arrival time series and that the effects of shocks are transitory. These results are interpreted as evidence for long-term sustainability in Malaysia's tourist sector.

Recently, Raza and Jawaid (2013) investigated the impact of terrorism on the tourism sector in Pakistan during the period of 1980–2010. The authors show using the Johansen and Jeuselius and ARDL (autoregressive distributed lag) bound testing cointegration approaches that terrorist attacks have a significant negative impact on tourism in both the long and short runs. More recently, Liu and Pratt (2017) measured the relationship between terrorism and tourism based on international demand models using panel data for 95 countries. Their findings indicate that globally, tourism is resilient to terrorism, with a limited impact in the short run. Interestingly, most of the literature on the terrorism–tourism nexus is based on annual time series or panel data. Agiomirgianakis, Serenis, and Tsounis (2017) argue that government actions and policies on tourism activities require being prepared for a quite short-term objective. Indeed, he stresses that political instability and terrorist upheavals, among other short internal or external factors, are often unpredictable for terms longer than 6–9 months. Furthermore, this timing dependence of policy decision makers (governmental and private) in the tourism industry is a problem the literature often fails to address. Our objective is to fill this gap fairly.

2.2. Persistence property of shocks on tourism demand

The second and more recent strand has focused on measuring the persistence property of shocks on international tourism demand. Instead of using unit root tests, most of the recent studies have investigated whether tourism activity series are characterized by a fractional integration parameter between zero and one.[1] Most of these studies have employed monthly or quarterly data of foreign tourist arrivals and/or overnight stays (Gil-Alana, 2005; Cunado, Gil-Alana, & de Gracia, 2008a; 2008b; Chu, 2008; and Gil-Alana, De Gracia, & CuÑado, 2004, 2008, 2014). Using quarterly data on the total number of arrivals in Kenya, Gil-Alana, Mudida, and de Gracia (2014) reveal that the series are fractionally integrated with an order above zero and below 1. Hence, they anticipate that shocks persistently fade slowly. Gil-Alana, Mervar, and Payne (2015) examine the presence of a long memory behavior in monthly foreign tourist arrivals and overnight stays in the Adriatic region of Croatia. Using parametric and semi-parametric fractional integration approaches, their findings reveal evidence for the persistence of shocks for most of the Croatian coastal counties.

However, several empirical studies have shown that it is important to be careful when examining and investigating the long memory property as this property can be spuriously created by structural changes that affect the short memory process (see Charfeddine & Guégan, 2012). This evidence of confusion between true and spurious long memory behavior was first revealed by Diebold and Inoue (2001), Gourieroux and Jasiak (2001), Granger and Ter︶svirta (1999), and Granger and Hyung (2004). In the tourism literature, many researchers have examined the presence of long-range behavior for many countries by exploring several tourism activity proxies (see Gil-Arana & Leon, 2008 among many others). Moreover, they have examined possible discrimination between a case where the long-range dependence behavior is true and the case of spurious behavior, which is created by neglecting breaks inside time series. Ohanissian, Russell, and Tsay (2008) argue that observing a long-range dependence behavior and discriminating between true and spurious behaviors are a difficult issue. Gil Arana and Leon (2008) and Mayral (2012) highlighted that the concepts of fractional integration and structural breaks are closely related issues. To account for both aspects, Gil-Alana et al. (2014) test the degree of persistence of the series with the presence of structural breaks, where the number of breaks and the dates are endogenously determined by the model.

2.3. Persistence of shocks and seasonality issues

Barros et al. (2016) stress the importance of correctly handling seasonality when measuring the persistence of shocks. Indeed, Song and Li (2008) argue seasonality is a striking feature of monthly or quarterly tourism data that needs to be considered when modeling and forecasting tourism demand. Gil-Alana, Cunado, and Perez de Gracia (2008) suggest that modeling the element of seasonality in a chronological series continues to be a controversial issue. Authors have considered deterministic and stochastic seasonality (seasonal unit roots and seasonally fractionally integrated models) when forecasting the number of tourists travelling to the Canaries Islands. Gil-Alana, Mervar, and Payne (2016) examined the impact of shocks on tourism in Croatia. They found that monthly foreign tourist arrivals and overnight stays contain seasonal unit roots, with the seasonally differenced components of the series allowing for transitory shocks to vanish relatively quickly. Ouerfelli (2008) applied a cointegration analysis and error correction models to study the profile of the European tourism market in Tunisia, based on quarterly tourist arrivals data from 1981:1 to 2004:4. Seasonal fluctuations in European tourism demand in Tunisia have been assessed using HEGY tests (Hylleberg, Engle, Granger, & Yoo, 1990) to test the presence of seasonal unit roots. The results show that these series exhibit non-stationary stochastic seasonality.

In the theoretical literature, the question of which method of deseasonalization should be used has been examined by many researchers, including Hood, Ashley, and Findley (2000), Franses, Paap, and Fok (2005) and many others. Hood et al. (2000) compare the ×12-ARIMA technique to the TRAMO/SEATS method. Their results show that overall these two techniques perform similarly for simulated series using 12 years of data. Moreover, TRAMO/SEATS perform better if the series is subject to large irregularities. The only case where ×12-ARIMA performs better is if the data sample is small. This result of similarity in terms of performance is also found by Franses et al. (2005, pp. 2005–2030). These researchers compare the performance of the TRAMO/SEATS, ×12-ARIMA, and Dianties methods using several DGPs. They find that TRAMO/SEATS and ×12-ARIMA perform well compared to the Dianties technique and whatever the DGP used. Moreover, their results show that the presence of additive outliers do not have a serious effect on the performance of these two methods. The authors recommend using one of these two techniques when there is no indication of the type of seasonality. In this paper, as our data spans more than 12 years, we propose the use of the TRAMO/SEATS technique; then, we propose using ×12-ARIMA as a robustness check.

3. The tourism sector in Tunisia

Historically and before the 2011 revolution, Tunisia was an attractive destination for many European countries, thanks to its affordability and close proximity to Europe. After its independence, the strategy of Tunisian tourism was exclusively targeted on the European Market in search for a nearby, safe, and affordable sun and sea destination. Presenting Tunisia as a safe and low-cost destination was a plan that succeeded in making it a player in the international tourism market for the last three decades. Carboni, Perelli, and Sistu (2014) mentioned that this strategy reinforced the dependence of the Tunisian tourism industry on European tour operators, which could undermine the Tunisian economy because of external shocks that may have an impact on employment and the external equilibrium. In the same vein, Jlassi et al. (2015) highlighted that the negative effects of the above-mentioned strategy rely in exposing the destination country Tunisia) to the shocks of the origin countries, such as the effect of the European crisis on tourism in Tunisia.

The tourism activity in Tunisia in the last two decades has shown high fluctuation, particularly during and after the periods of political instability or terrorists attacks. For instance, since the Jasmine revolution of January 2011, there has been a sharp fall in most of the Tunisian tourism indicators. For instance, between 2010 and 2015, the number of tourist arrivals, tourist overnight stays, and tourism receipts fell by 31.5%, 54.5%, and 33.2%, respectively (Authors' calculation based on data provided by the national institute of statistics of Tunisia.). Moreover, since 2010, the Tunisian economy has been subject to several local and international shocks, including several national, regional, and international shocks, for example, terrorist attacks against Tunisian national polices and several tourist sites, the Egyptian and Libyan revolutions, and several other shocks that have threatened the overall activity of the sector. This sharp fall in most of the tourism indicators during the last few years, combined with several regional and local events (terrorist attacks), have motivated us to examine the effects of these recent political and terrorist attacks on tourism activity. This

[1] Shocks are considered as persistent, in the sense that they have long-lasting effects, if the estimated fractional degree of differentiation of the series, d, lies above zero and below one. In the case when $d = 1$, the effect of shocks are permanent. If the fractional long memory parameter d is not significantly different from zero, then the impact of shocks on the tourism activity will vanish and die after a few observations (a few months in our case). For more details, see Charfeddine and Guégan (2012), who summarize the difference between unit root tests, unit root tests with breaks, and the fractional integration procedure.

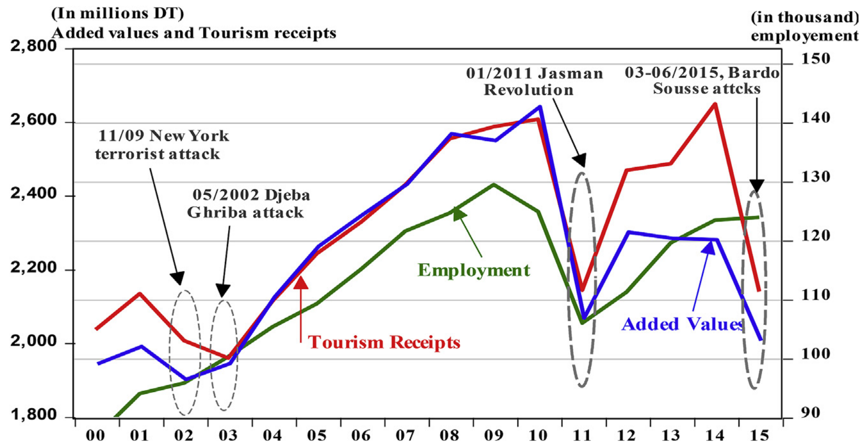

Fig. 1. Trends in Tunisian tourism indicators in Tunisia. 2000–2015.
Source: Authors calculations and Tunisian National Institute of Statistics.

examination will help us to propose some economic, security and marketing policies that may help to restore Tunisian tourism activity.

Fig. 1 shows the trend in some tourism activity indicators in Tunisia for the period from 2000 to 2015. This figure sheds light on the question of whether terrorist activities have an impact on the tourism industry. The slowdown of tourism receipts and tourism GDP from 2002 to 2003 is explained by the aftermath of September 11 and the effect of the June 2002 terrorist attack in Djerba. In the immediate aftermath of more recent events, including the 2011 revolution, the drop in tourism activities exacerbated structural issues, including a lack of diversified offerings and the tourism industry's over-dependence on European markets. In 2015, another drop in tourism activities was observed following two terrorist incidents: in March at the Bardo Museum in Tunis and in June at the Resort in Sousse. During 2015, tourist arrival fell to 5.5 million, the lowest level in decades, and tourism revenues fell 35% to USD1.5 billion. According to the ministry of tourism, the fall in tourism revenues contributed to a slowdown in economic growth to 0.8% from 2.3% a year earlier. It is interesting to note, from Fig. 1, that external shocks (such as the September 11 terrorist attack or the financial crises in 2008) had a moderate impact on Tunisia's tourism activity in comparison with internal events (such as the political instability after the Jasmine Revolution in 2011 or the terrorist attacks in 2015). This underscores the business strategy of anticipating disturbances in the tourist landscape because of terrorist attacks, which may adversely affect tourism activity and have negative social consequences in terms of job losses and poverty acceleration. Unfortunately, graphic analyses do not distinguish between the impact of political violence and terrorist attacks, both of which seem to have severe consequences for tourism activity.

4. Data and preliminary analysis

The aim of this section is to determine the true data generating process of the tourist arrival series. To this end, several statistical properties of the tourist arrival series will be examined in the next subsections. These properties include seasonality, trends, unit roots, structural breaks, long memory, and spurious long memory.

In subsection 4.1, we will investigate all these properties from a descriptive point of view. We will do this by analyzing the trajectory, autocorrelation function (ACF) and spectral density of the number of tourist arrivals. Then, in subsection 4.2, we will employ several testing procedures to determine the true data generating process of the number of tourist arrivals. In particular, we will test for three important properties: (1) unit root with structural breaks, (2) long memory, and, finally, and (3) true versus spurious long memory.

4.1. Data description

The dataset used in this study consists of monthly data for the number of international tourist arrivals in Tunisia from January 2000 to September 2016, which were collected from the Tunisian National Institute of Statistics from monthly publications: “Bulletin mensuel de statistique”. Annual data regarding tourism activities, such as tourism receipts, investments, occupation rates, and nights, can be found at http://dataportal.ins.tn/. Fig. 2 displays the trajectory, autocorrelation function, and spectral density of the seasonally unadjusted (Panel A) and seasonally adjusted (Panel B) series.

From Panel A, and specifically from the trajectory of the seasonally unadjusted monthly number of tourist arrivals, we observe that these series are characterized by three main statistical properties: (1) seasonality, (2) structural changes, and (3) trends.

The first property of seasonality, defined by the presence of a regular fluctuation in the number of tourist arrivals, is observed in the trajectory in months June, July, and August. During these months, the number of tourist arrivals reached its highest levels, a result that is expected as these three months correspond to the periods of the tourist summer season and summer vacation of almost all the European countries and Tunisia neighbor countries (Algeria and Libya).

The second statistical property, the presence of structural changes, is also visually observed in the trajectory of the number of tourist arrivals, in which at least two sudden changes are observed. The first break coincides with approximately the end of the year 2010 and the second one coincides with mid-year 2015. From a political view point, these two breaks seem to be associated with the Tunisian Jasmine revolution of January 2011 and the recent two terrorist attacks in March and June 2015 against the Bardo National Museum and the hotel of Port of Kantaoui, Sousse. For instance, as shown in the introduction, the Jasmine revolution and the last two terrorist attacks in Tunisia have severely impacted the tourist sector, particularly the number of tourist arrivals.

Finally, the last property that characterizes the number of tourist arrivals is the trend property, which is observed in the trajectory of the seasonally unadjusted tourist arrival series. For instance, the trajectory of this later series shows clear evidence for the presence of an upward trend during all periods of study. In particular, the trajectory shows evidence of the presence of at least three upward trends that seem to characterize the tourist arrival series. The first trend characterizes the period from January 2000 to January 2011, the second characterizes the period from January 2011 to March 2015; and the third characterizes the rest of the period of study.

Moreover, in addition to all three properties, the ACF and spectral density of the tourist arrival series show that these data may be

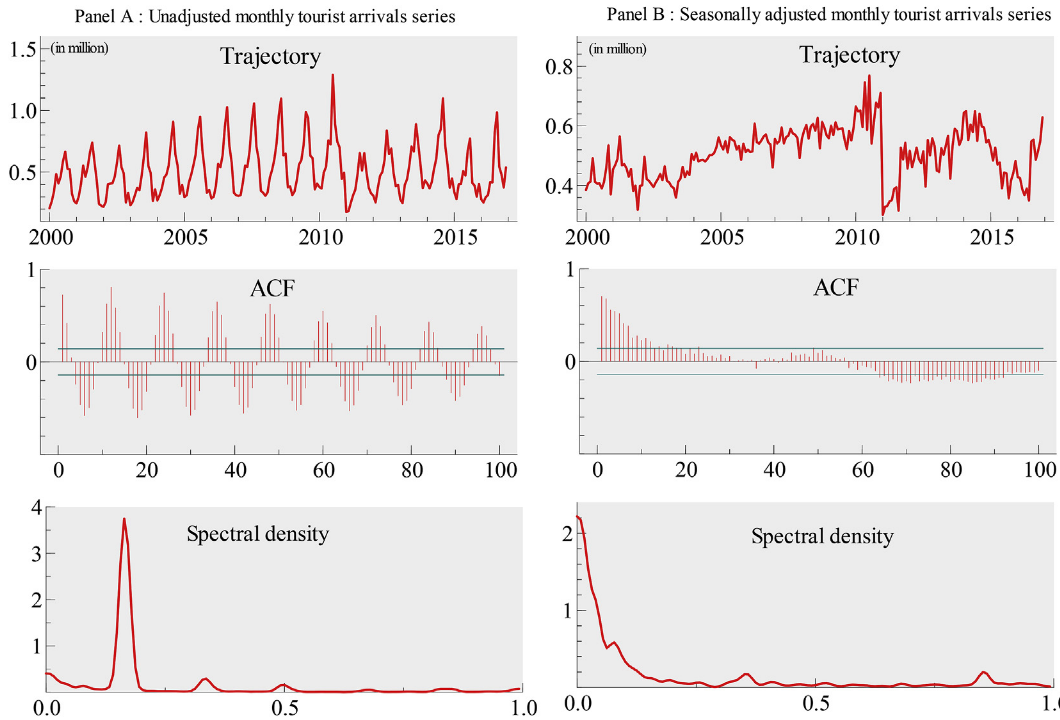

Fig. 2. Trajectories, Autocorrelation function (AFC) and spectral density of the monthly number of adjusted and unadjusted tourist arrivals series.

characterized by of the presence of a long memory component. Evidence for the presence of this property is observed and detected by visual analysis of the autocorrelation function (ACF), which decays slowly to zero, and the spectral density, which shows peaks at different frequencies.

In addition to the trajectory, ACF and spectral density graphics reported in Panel A for the original series, we report in Panel B these same graphics but for the seasonally adjusted number of tourist arrivals. To remove the seasonal component, we use the TRAMO/SEATS procedure. The use of this method is motivated by its superiority compared to other approaches, including the well-known X-12-ARIMA technique (Franses et al., 2005, pp. 2005–2030). Moreover, we use X-12-ARIMA as a second technique of de-seasonality to increase the robustness of our results. The use of the second method is motivated by the empirical findings of Barros et al. (2016), who found that if seasonality is not accurately managed, then the persistence of shocks will not be appropriately resolved. Our empirical results show that after removing seasonality from the original series, the new trajectory shows the same evidence for the presence of both structural breaks and trends. Overall, there are no strong changes compared to the results from the original series. In particular, the trajectory shows clear evidence that the number of tourist arrivals was volatile between January 2000 and mid-2003, followed by a continuous increase until January 2011. Between January 2011 and July–August 2011, there was a significant and intense decline in the number of monthly tourist arrivals, which can be explained by the effects of the Jasmine revolution, which lasted from December 2010 to January 2011. Finally, we observe an increase in the number of tourist arrivals until mid-2015, at which point a new drop is observed until the end of the period of our study. The economic explanation of the break dates are as discussed above.

To account for all these statistical properties, we propose in the next section a statistical procedure that allows us to ascertain the true DGP of the tourist arrival series. This testing procedure will make use of several tests' statistics, including unit root tests with and without breaks, and tests for true versus spurious long memory behavior.

4.2. Data generating process (DGP) of the tourist arrivals

To build and design appropriate strategies and/or policies that allow Tunisian policymakers to restore the tourism activity of the country in an efficient way, it is of primary importance to determine the true DGP of the tourist arrivals time series. For instance, the extent of the impact of shocks in term of duration and magnitude differs significantly depending on the true DGP of the tourist arrival series. Therefore, it is very important to test the two extreme cases of transitory versus permanent and the two cases of long memory versus short memory with structural breaks (Diebold & Inoue, 2001; Huang and Geweke & Porter-Hudak, 1983; and; Charfeddine & Guégan, 2012).

In this study, we propose an empirical strategy defined in four steps to determine the true DGP of the series under study:

1. First, we begin our analysis by testing for whether the impact of shocks on the number of tourist arrivals is transitory against the case where shocks have a permanent effect. To investigate these two possibilities, we employ both unit root tests with and without structural breaks. More precisely, we use four traditional unit roots tests as developed by Ng-Perron (1995) and their counterparts that allow for multiple unknown breaks up to five breaks under both the null and the alternative hypothesis (see Charfeddine & Guégan, 2011).
2. Then, we use several long memory estimation methods and test statistics to validate the evidence of long memory observed in the ACF and spectral density. These methods and tests include the modified R/S test of Lo (1991), the rescaled variance (V/S) test of Giraitis, Kokoszka, Leipusc, and Teyssiere (2003), the Geweke and Porter–Hudak (Geweke & Porter-Hudak, 1983) test, the Gaussian semi-parametric (GSP) test of Robinson and Henry (1999), the Local Whittle (LW) test of Robinson (1995), the exact local whittle (ELW) test of Shimotsu and Phillips (2005), and the 2-step exact local Whittle (2SELW) test of Shimotsu (2006b). All these methods and tests are used to explore the long memory behavior observed in the ACF and spectral density.
3. Third, we infer and test, by using the sample splitting test of

Shimotsu (2006a), the two behaviors of short memory with structural breaks (Charfeddine & Guégan, 2011) and long-range dependence. The outcomes of this step will provide us with the true DGP of the number of tourist arrivals.

4. Finally, based on the results obtained in 3, a flexible autoregressive Markov switching model or a long memory model will be employed to better model the number of tourist arrivals. However, based on the results of section 4, a Markov switching model where the intercept, trend, and variance all switch between regimes seems to be more appropriate for modeling the number of tourist arrivals in Tunisia.

4.2.1. Unit root tests with breaks

One of the merits of applying unit root tests to the number of tourist arrivals is the ability to distinguish between the two extreme behaviors of transitory and permanent effects of shocks. Econometrically, evidence of stationarity for the tourist arrival series indicates that the effect of shocks will be transitory, i.e., the impact will vanish after a few observations (a few months in our case). In contrast, a non-rejection of the null hypothesis of unit root means that the impact of shocks is permanent and strong policies should be implemented to restore tourism activity.

To examine the transitory versus permanent effects of shocks on tourism activity, proxied by the number of tourist arrivals, we use both the traditional unit root tests of Ng-Peter, Poulston, and Losekoot (2014) and the unit root tests with structural breaks of Carrion-i-Silvestre, Kim, and Perron (2009) . The main motivation behind the use of unit root tests with structural breaks lies in the fact that ignoring the presence of breaks in the tourist arrival series, when testing for the presence of unit root, can introduce a misleading and incorrect interpretation of the results. For instance, traditional unit root tests are known to suffer from low power when the time series under study are subject to structural breaks. Moreover, the unit root tests of Carrion-i-Silvestre et al. (2009) have the advantage of considering the case of unknown multiple structural changes up to five breaks under both the null and alternative hypotheses.[2] These advantages will help us better understand whether shocks on the tourist arrival series will be transitory or permanent.

Four traditional unit root tests of Ng-Perron (1995) and their counterpart unit root tests with structural breaks, as developed by Carrion-i-Silvestre et al. (2009), will be used in this study. These latter tests include the $MZ_{\alpha}^{GLS}(\lambda)$, $MSB^{GLS}(\lambda)$, $MZ_{t}^{GLS}(\lambda)$, and $MP_{T}^{GLS}(\lambda)$ tests, where λ is the break point parameter. The limiting distribution and critical values of all these tests are obtained by simulation (a detailed description of all these tests is presented in the supplementary document).

The results of applying both types of unit root tests on the time series of the number of tourist arrivals are reported in Table 1. The results of the Ng-Perron (1995) unit root tests reported in Panel A show mixed evidence regarding the stationarity hypothesis. For instance, whereas $\mathrm{MZ}_{\alpha}^{\mathrm{GLS}}$ and $\mathrm{MSB}^{\mathrm{GLS}}$ show strong evidence of stationary using the intercept with/without trend specification, the $\mathrm{MZ}_{\mathrm{t}}^{\mathrm{GLS}}$ and $\mathrm{MP}_{\mathrm{T}}^{\mathrm{GLS}}$ statistics do not reject the hypothesis of unit root when allowing for an intercept and trend.

The empirical results of the unit root tests of Carrion-i-Silvestre et al. (2009), reported in Panel B of Table 1, show that the hypothesis of

Table 1
Unit root with and without structural changes for logarithm of arrivals.

Panel A: Unit root without structural breaks

	With intercept		With intercept and trend	
	Statistics	C·V	Statistics	C·V
MZ_{α}^{GLS}	−7.149	−8.100	−16.931	−17.300
MZ_{t}^{GLS}	−1.809	−1.980	−2.9074	−2.9100
MSB^{GLS}	0.253	0.233	0.1717	0.1680
MP_{T}^{GLS}	3.726	3.170	5.3954	5.4800

Panel B: Unit root with structural breaks

	Crash model (shifts in level only)			Shifts in level and slope of the trend		
	Statistics	C·V	Breaks dates	Statistics	C·V	Breaks dates
$MZ_{\alpha}^{GLS}(\lambda)$	−47.968	−38.819	2001-M09 2003-M01 2011-M01 2011-M09 2016-M06	−57.996	−38.802	2001-M09 2011-M01 2011-M09 2014-M06 2015-M06
$MZ_{t}^{GLS}(\lambda)$	0.1020	0.1149		0.0928	0.1139	
$MSB^{GLS}(\lambda)$	−4.8943	−4.3865		−5.3848	−4.3971	
$MP_{T}^{GLS}(\lambda)$	6.2293	7.9071		5.1331	7.8227	

stationarity with structural breaks, the I(0) process, cannot be rejected regardless of the unit root tests used and specification employed (intercept with or without trend). This evidence of stationarity indicates that the effect of shocks on tourist arrivals is transitory with evidence of structural breaks.

In particular, the results show that the series of the number of tourist arrivals is characterized by the presence of five breaks. Interestingly, these break dates correspond to several political events and terrorist attacks. In particular, we found evidence of a significant effect for the September 11 (2001) terrorist attack in New York City, the January 2011 Jasmine revolution in Tunisia, and the recent terrorist attacks at the Bardo National Museum and the Sousse Port Kantanoui hotels between March 2015 and May 2015. This result confirms our preliminary analysis based on the trajectory of the number of tourist arrivals.

4.2.2. The long memory property

i Definition of long memory

As mentioned above, one of the properties to be explored is the property of long memory. In the econometric literature, there are two possible definitions of long memory. The first is a time domain definition. Following this definition, a time series (Y_t), $t = 1, \ldots, T$ is said to display a long memory behavior if its autocorrelation function decays slowly (hyperbolically) towards zero. In a mathematical presentation, the autocovariance function of Y_t will be

$$\gamma_k \approx c(k)\, k^{2d-1}, \tag{1}$$

where d is the fractional long memory parameter. If $0 < d < 1$, the process is a long memory process, if $0 < d < 1/2$, the long memory process is stationary, and if $1/2 < d < 1$, the long memory process is nonstationary but mean-reverting. $c(k)$ is a slowly varying function at infinity.

The second definition of long memory is a frequency domain definition. In this case, the series (Y_t) exhibits a long memory if the spectral density explodes at frequency near zero. The frequency domain definition of long memory is given by

[2] Compared to the several unit root tests with structural breaks, such as the tests of Zivot and Andrews (1992), Lee and Strazicich (2003), and Lumsdaine and Papell (1997), the unit root tests with structural breaks proposed by Carrion-i-Silvestre et al. (2009a) have the advantage of considering the case of multiple breaks where the dates of these breaks are unknown (endogenously determined). The maximum number of breaks allowed under these tests is five breaks. Moreover, compared to the majority of previous tests in the empirical literature, except those of Lee and Strazicich (2003), these tests assume the presence of breaks under both the null and alternative hypotheses.

Table 2
Estimation of the fractional long memory parameter for the tourist arrivals time series.

q	Non-parametric tests		m	Parametric tests				
	Modified R/S	V/S		GPH	GSP	LW	ELW	2S-ELW
1	2.8893***	0.9210***	$T^{0.5}$	0.5823***	0.5507***	0.2598***	0.9416***	0.5845***
5	1.9877**	0.4255***	$T^{0.6}$	0.7898***	0.6338***	0.1829**	0.9298***	0.6443***
10	1.4512	0.2401**	$T^{0.7}$	0.7362***	0.5720***	0.1354*	0.9989***	0.9320***
20	1.2708	0.1594	$T^{0.8}$	0.7485***	0.5701***	0.1082	0.9928***	0.6067***

The critical values of the Modified R/S statistic see Lo (1991) and for the critical values of the V/S statistic see Giraitis et al. (2003).
The critical values of the GPH, GSP, LW, ELW and 2S-ELW statistics are those of the standard normal distribution, 1.645, 1.96 and 2.58 for the 10%, 5% and 1% respectively.
*,**,*** stand for significance at the 10%, 5% and 1% level of significance respectively.

$$f(\omega) \approx \infty \text{ as } \omega \text{ tends to zero} \tag{2}$$

ii Testing for long memory

To test for long memory behavior in the tourist arrival series, we propose the use of two non-parametric tests statistics of long memory, namely the modified R/S and V/S statistics and five semi-parametric estimation methods of the fractional long memory parameter d. These later methods include the GPH, GSP, LW, ELW, and 2SELW estimation techniques. The estimation results are also reported in Table 2, where different values of truncation lag parameter are used. For the two nonparametric statistics, we use q = 1, 5, 10, and 20. For the parametric tests statistics, we use $m = T^k$, where $k = 0.5, 0.6, 0.7, 0.8$ and T is the number of observations.

The results show that the number of tourist arrivals is characterized by the presence of long memory behavior. For instance, five out of the eight calculated statistics of the modified R/S and V/S tests show evidence for the rejection of the null hypothesis of short memory against the alternative of long-range dependence. In contrast, 18 out of the 20 estimated fractional long memory parameters, using the parametric tests, are significantly different from zero.

In terms of economic significance and implications, evidence of the presence of long-range dependence, if it is a true behavior, indicates that shocks affecting the number of tourist arrivals have long-lasting effects and their effects do not disappear rapidly. However, it is worth noting that before continuing with the discussion of the economic interpretation and the policy implications of this latter result, it is important to examine whether this long memory behavior is true and not spuriously created by the presence of structural breaks (see Diebold & Inoue, 2001; Huang and Geweke & Porter-Hudak, 1983).

Indeed, we need to be cautious, as many empirical studies have shown that the existence of breaks can be attributed to the existence of a long memory behavior in the time series and that these breaks are spurious (Beran, 1994). In contrast, several other studies have shown that long-range dependence behavior can be created by the presence of breaks inside these series (Diebold & Inoue, 2001; Huang and Geweke & Porter-Hudak, 1983; and; Charfeddine & Guégan, 2012; Walther, Klein, Thu, & Piontek, 2017). To investigate this issue of true versus spurious long memory, we propose the use of the splitting sample test of Shimotsu (2006a), which is designed to distinguish between short memory with breaks (spurious long range dependence) and true long-range dependence behavior. The results of this test will help us to be clear cut in term of the distinction between these two different behaviors and in determining the true data generating process of the number of tourist arrivals.

4.2.3. *Shimotsu (2006a) test of true versus long-range dependence*

The Shimotsu (2006a) test consists of splitting the tourist arrivals time series into b subsamples and in comparing the estimated long memory parameter d of the entire sample to the estimated fractional long memory parameter of each subsample. The idea of this test is based on the following assumption: If the observed long memory behavior is a true behavior, then the estimated fractional long memory parameter of d for the full sample should not be significantly different from those estimated from the subsamples.

The null hypothesis of the true long memory $I(d)$ is as follows:

$$H_0\text{: True long memory}(H_0\text{: } d = d^{(1)} = \ldots = d^{(b)}) \tag{3}$$

The alternative hypothesis corresponds to the following:

$$H_1\text{:Short memory affected by breaks} \tag{4}$$

where $d^{(i)}$ for $i \in \{1,2,\ldots,b\}$ is the true value of the fractional long memory parameter from the ith subsample and d is the true value for the full sample.

The test statistic proposed by Shimotsu (2006a) is called the W_c test, which has a chi-squared limiting distribution with $b-1$ degrees of freedom (see the Appendix for a full description of the test).

The results of the splitting sample test (W_c) of Shimotsu (2006a) are reported in Table 3. We use the values of $b = 5$ and $b = 6$. These choices are based on the number of breaks selected in the previous section: five breaks ($b = 6$). We also consider the case where the number of breaks is 4 ($b = 5$). The results of the W_c test show that the hypothesis of true long memory behavior is rejected whatever the value of the parameter of truncation m and for both values of b. We confirm the results of the previous section, which indicate that the DGP for tourist arrivals is a short memory process that has been subject to several structural breaks.

5. A markov switching model for the number of tourist arrivals

Once the evidence for stationarity with structural breaks for tourist arrivals has been approved and well established, the next step consists of modeling the tourist arrivals time series by using models that can account for both short memory and structural breaks. In econometric theory, several models have been proposed to account for these two behaviors, which include the threshold autoregressive models (TAR) of Tong (1990) and their different extensions (Terasvirta, 1994; and; Terasvirta & Yang, 2014), the structural change models (Quandt, 1958; and Bai & Perron, 1998, 2003), and the Markov switching model of Hamilton (1989). Several other models exist that take into consideration the two behaviors of short memory and breaks. These models

Table 3
Shimotsu (2006a) test for true versus spurious long memory for the number of tourist Arrivals.

Shimotsu (2006a) Splitting sample test (W_c)		
	m	Logarithm of Number of tourist Arrivals
$b = 5$	20	**10.322****
	40	**15.083*****
$b = 6$	20	**15.173*****
	40	**18.519*****

include the mean-plus-noise model of Diebold and Inoue (2001), the sign model of Terasivirta and Geweke and Porter-Hudak (1983) and the STOPBREAK model of Engel and Smith (1999), among many others.

In this study, we propose the use of a general form of the Markov switching autoregressive model where all the parameters, except the autoregressive order, are allowed to switch between regimes. We choose the Markov switching autoregressive model because it encompasses most of the models presented above as a special case (see, for instance, Krolzig, 1997; Carrasco, 2002; and Charfeddine & Guégan, 2008).

5.1. The Markov switching autoregressive model

Because the hypothesis of true long memory was rejected using Shimotsu (2006a) test against the alternative of short memory with breaks, the next step consists of using models that take into consideration short memory and changes in regimes. We propose the use of the Markov switching Autoregressive ($MS(k) - AR(p)$) model with changes in both the mean and variance, where k represents the number of regimes and p is the autoregressive order.

The general form of the $MS(k) - AR(p)$ model is given by the following:

$$y_t = \mu_{s_t} + \delta_{s_t} @trend + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sigma_{s_t} u_t \tag{5}$$

where s_t is a dummy variable that takes values of 1, 2 and 3. It is governed by a first-order Markov chain that is given by the following:

$$S_t = \begin{cases} 1 \textit{with probability } p_{11} \\ 2 \quad \textit{with probability } p_{22} \\ 3 \quad \textit{with probability } p_{33,} \end{cases} \tag{6}$$

where

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{12} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \quad \text{and} \quad \sum_{j=1}^{3} p_{ij} = 1 \tag{7}$$

Under these notations, the intercept and slope coefficients can be written as follows:

$$\mu_{S_t} = \mu_1\, S_{1t} + \mu_2\, S_{2t} + \mu_3\, S_{3t} \tag{8}$$

and

$$\sigma_{S_t}^2 = \sigma_{S_t}^2 S_{1t} + \sigma_{S_t}^2 S_{2t} + \sigma_{S_t}^2 S_{3t} \tag{9}$$

where $S_{kt} = 1$ if $S_t = k$ and $S_{kt} = 0$; otherwise, $k = 1,2,3$.

To select the most appropriate specification of the $MS(k) - AR(p)$, we proceed in the following way:

1. First, the automatic model selection technique, which is implemented by using the generic-to-specific (*Gets*) approach, is used to select the most appropriate autoregressive lag order. The main advantages are that it cannot be outperformed even by an expert in econometrics and it is not time consuming. The automatic implementation of the *Gets* technique requires only the selection of the initial model presentation, known in the literature as the general unrestricted model, and then the computer will select the more appropriate presentation by checking the validity of each model reduction using a large number of residual-based test statistics.
2. The selected AR(p) specification will be used as the starting point for estimation procedure of the Markov switching autoregressive model, $MS(k) - AR(p)$. Several specifications of the $MS(k) - AR(p)$ model will be examined by allowing the intercept, trend, autoregressive order coefficients and variance to depend on the state of the economy, S_t. Note that in this study, we examined several variance specifications (fixed variance, variance switching, GARCH switching, mean-variance component). However, as we use a non-financial time series, we expect that the GARCH switching and mean-variance component will not fit the variance structure of our data.
3. To select between the linear $AR(p)$ and the Markov switching autoregressive model $MS(k) - AR(p)$ and between different $MS(k) - AR(p)$ models, we use the log-likelihood ratio (LR) test. An important remark is that the LR test has a non-usual limiting distribution under the null hypothesis. To solve this problem, Davies (1977, 1987) proposed a bound test approach that allows us to test the linear versus Markov switching specification. Hansen (1992) and Garcia (1998) also developed other tests statistics and approaches (see Charfeddine & Guégan, 2011 and 2012).
4. Finally, after selecting the adequate Markov switching autoregressive model, to assess the quality of the fitted model, we use the regime classification measure (RCM) of Baele (2005):

The RCM is given for K > 0 states by the following:

$$RCM(K) = 100 * \left(1 - \frac{K}{K-1} \frac{1}{T} \sum_{t=1}^{T} \sum_{h=1}^{K} \left(p_{i,t} - \frac{1}{K}\right)^2\right) \tag{10}$$

where $p_{i,t} = \Pr[S_t = i | I_T]$ is the probability of being in regime i at time t. The *RCM* measure lies between 0 and 100. The decision rule when using this measure is that if the true DGP is a Markov switching model, then the diagonal elements of the transition probabilities matrix will be close to the unit, which makes the *RCM* measure close to zero. In contrast, if the DGP is not a Markov switching model, then the *RCM* will be close to 100.

A second tool used to assess the quality of the selected Markov switching model is to analyze and compare its residuals properties, in terms of the absence of autocorrelation and homoscedasticity, to the linear and $MS(2) - AR(p)$) models.

An important issue that arises when using the Markov switching models is that the maximum log-likelihood technique can encounter several local optimums, rather than a unique global optimum (see Hamilton, 1989, 1990). To solve this problem, Hamilton (1989) suggests using several starting values. In this study, we use more than 1000 starting values for each estimated specification to guarantee that the maximum obtained is a global one.

5.2. Markov switching model selection and interpretations

5.2.1. Model selection

Estimating the Markov switching model involves selecting the lag parameter p and the parameters that switch between regimes and determining the number of regimes. The value of autoregressive lag p is selected using the automatic model selection technique implemented via the *Gets* approach, which shows that a first-order autoregressive model is enough for this time series to remove the presence of autocorrelation. The results also show that by estimating different specifications of the $MS(k) - AR(1)$ model, there is strong evidence for switching in the intercept, trend, and variance. This evidence of intercept and trend parameter switching confirms the results previously obtained by the Charfeddine and Guégan (2011) unit root tests with structural changes.

The results of the LR test for testing between linear versus $MS(2) - AR(1)$ and between the models $MS(2) - AR(1)$ and $MS(3) - AR(1)$, reported in Table 4, support the alternative hypothesis of $MS(2) - AR(1)$ against the null hypothesis of a linear model, and the alternative hypothesis of $MS(3) - AR(1)$ against the null hypothesis of $MS(2) - AR(1)$.[3] This result of the superiority of the $MS(3) - AR(1)$

[3] Testing between different numbers of regimes in the Markov switching model remains a very complicated task for several problems, such as the existence of nuisance parameter under the null hypothesis, identically zero scores and the existence of several local maxima. Davies (1977, 1987) proposed an

Table 4
Estimation of the linear, Markov switching with 1 and 2 breaks.

	Linear Model		MS(2)-AR(1)		MS(3)-AR(1)	
	Coef.	t-stat	Coef.	p-value	Coef.	p-value
Models Parameters estimations						
μ_1	2.4414	0.000	0.8068	0.127	10.737	0.000
μ_2	–	–	1.1295	0.004	10.628	0.000
μ_3	–	–	–	–	10.118	0.000
φ_1	0.8124	0.000	0.9141	0.000	0.1695	0.000
@trend1	9.724e-05	0.440	0.0022	0363	0.0022	0.000
@trend2	–	–	−4.67e-05	0.598	0.0017	0.000
@trend3	–	–	–	–	0.0030	0.000
σ_1	0.0924	0.000	0.3524	0.000	0.0410	0.000
σ_2	–	–	0.0607	0.000	0.0714	0.000
σ_3	–	–	–	–	0.0762	0.000
p_{11}	–	–	0.9617	0.000	0.9837	0.000
p_{12}	–	–	–	–	0.0130	0.438
p_{21}	–	–	–	–	0.0084	0.755
p_{22}	–	–	0.6712	0.000	0.9667	0.000
p_{32}	–	–	–	–	0.0130	0.459
p_{33}	–	–	–	–	0.9570	0.000
Log. L	181.958		202.499		254.278	
LL ratio (LR)			41.082		103.558	
RCM	–		8.355		1.840	
AIC	−1.8831		−2.3757		−2.5320	
SC	−1.8145		−2.2384		−2.2748	
Residuals Analysis						
Mean	0.0000		−6.026e-07		1.647e-08	
Std. dev	1.0000		0.0024		0.9786	
J-Bera	124.3 (0.0000)		0.0128 (0.9936)		4.8301 (0.0894)	
QB(12)	27.00 (0.0000)		19.448 (0.0783)		11.306 (0.5028)	
QB2(12)	15.496 (0.2154)		17.319 (0.1379)		13.955 (0.3036)	
ARCH(12)	3.4014 (0.0002)		2.8625 (0.0014)		1.3775 (0.1824)	

specification is also confirmed by the RCM criterion, which is the closest to zero, e.g., 1.840. For instance, the RCM criterion indicates small values for both the $MS(2) - AR(1)$ and $MS(3) - AR(1)$ specifications, compared to the value of 100 when the true DGP is a linear model. Moreover, by comparing the RCM of the two specifications, the $MS(3) - AR(1)$ and $MS(2) - AR(1)$ models, the results show that the $MS(3) - AR(1))$ model is more appropriate and fits the evolution of the tourist arrival time series better; e.g., the RCM of the $MS(3) - AR(1)$ model is equal to 1.840, which is lower than the value of 8.355 for the $MS(2) - AR(1)$ model.

In addition to the previous LR tests and RCM criteria, we compared these three models based on their residuals properties. The results of the residual analysis, reported at the bottom of Table 4, show that $MS(3) - AR(1)$ is the only specification where the hypothesis of the absence of autocorrelation and homoscedasticity cannot be rejected.

To summarize, the different tests and techniques used to select the model that best fits the tourist arrival time series support with strong evidence a Markov switching model with three states in the intercept, trend, and variance.

5.2.2. Interpretation of the 3S-MS-AR(1) model

Turning now to the interpretation of the results of the 3S-MS-AR(1) selected model, the results show that all the estimated coefficients (μ_1, μ_2, μ_3, φ_1, δ_1, δ_2, δ_3, σ_1^2, σ_2^2, σ_3^2, and p_{ii}) for $i = 1, 2, 3$ are highly significant at the 1% level of significance.

The results reported in Table 4 can be interpreted as follows:

1. Regime 1 corresponds to the period where Tunisian tourist activity is characterized by a period of tourism activity expansion and where the number of tourist arrivals is at its highest level. For instance, regime 1 has the highest value of the estimated intercept coefficient, $\mu_1 = 10.737$, the lowest value of volatility, $\sigma_1^2 = 0.041$, and an estimated coefficient for the upward trend that it is not well pronounced, $\delta_1 = 0.0022$. Economically, this regime corresponds to a period of economic expansion and periods where the local political environment is stable.
2. Regime 2 corresponds to the period where Tunisian tourism activity is—on average—high: the estimated intercept coefficient is $\mu_2 = 10.628$. However, the period of regime 2 is characterized by a high level of volatility, $\sigma_2^2 = 0.0714$, compared to the first regime. This means that this regime corresponds to an intermediate regime characterized by an average level of tourist arrivals that is similar to that of regime 1 and by a level of volatility that is similar to that of regime 3. In terms of trend evolution, this regime has the lowest trend coefficient of $\delta_2 = 0.0017$. This regime corresponds to the periods after September 11th, 2001; after the Jasmine revolution and after the recent terrorist attacks of 2016.
3. The results show that regime 3 corresponds to the period in which the Tunisian tourism activity is in its lower level (period of recession). This regime is characterized by the lowest estimated value of the intercept coefficient, $\mu_3 = 10.118$, and the highest value of the variance, $\sigma_3^2 = 0.0762$, compared to the two previous regimes. However, this regime is characterized by the highest estimated trend coefficient, i.e., $\delta_3 = 0.0030$. Economically, this regime corresponds to the period in which the tourism sector was subject to important negative shocks, such as the period of the Jasmine revolution and the period of the two terrorist attacks of 2015.

For all three regimes, the type and exact dates of these shocks will be discussed and analyzed in the next section.

Now, once the specification $MS(3) - AR(1)$ has been approved as the most accurate and appropriate specification to describe the evolution of the tourist arrivals time series, we will focus our analysis on the economic interpretations and the economic and management implications of these results.

This will be discussed first on the basis of the regime classification and then on relaying the dates of the breaks of the major political shocks and terrorist attacks that have affected Tunisia.

5.3. Probabilities smoothing and regime classification analysis

As discussed previously, the smoothed probability for each regime is the tool used to date the breaks (see Hamilton, 1989). The smoothed probabilities for the selected $MS(3) - AR(1)$ model are reported in Fig. 3. The first box, in the top left, reports the time series of actual seasonally adjusted monthly tourist arrivals in red and the three regime periods in the shaded area. These three shaded areas are also presented in the three other boxes with a box for each regime duration. From Fig. 3, we can conclude that the number of tourist arrivals in the first regime is more stable in terms of duration and variability compared to the two other regimes, followed by regime 2 and lastly regime 3. Moreover, Fig. 3 shows clear evidence that regimes 2 and 3 are more volatile than regime 1 and that regime 3 is characterized by the lowest level of the number of tourist arrivals.

In addition, the results of the regime classification reported in Table 5 show that the first regime spans exactly 8 years and 10 months (106 months), divided into two sub-periods where the first sub-period spans 21 months and the second spans 85 months. The second regime spans 73 months, divided into three sub-periods of 26 months for the

(*footnote continued*)
upper bound test to determine the number of regimes. Hansen (1992) used empirical process theory to bound the asymptotic distribution of the standardized Likelihood Ratio statistic. Then he used the simulation to determine the critical values for some cases of a Markov switching process based on the grid search technique. Garcia (1998) tabulated some critical values for the 2-State-MS-AR models under some particular assumptions.

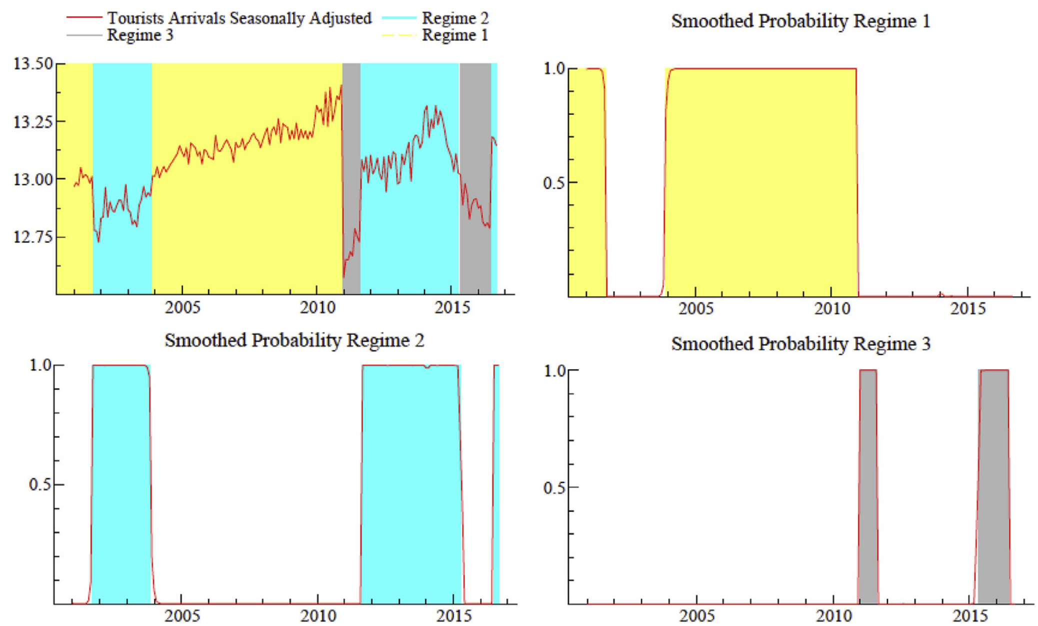

Fig. 3. Monthly number of tourists arrivals and probabilities smoothing from the. $MS(3) - AR(1)$

Table 5
Regime classification and duration based on smoothed probabilities.

Regime	Starting date	Ending date	Duration
Regime 1	2000-M01	2001-M09	21 Months (1 year and 9 month)
	2003-M12	2010-M12	85 Months (7 years and 1 month)
Regime 2	2001-M10	2003-M11	26 Months (2 years and 2 months)
	2011-M09	2015-M04	44 months (3 years and 8 months)
	2016-M07	2016-M09	3 months
Regime 3	2011-M01	2011-M08	8 months
	2015-M05	2016-M06	14 months (1 year and 2 month)

first sub-period, 44 months for the second sub-period and 3 months for the last sub-period. Finally, the last regime spans 22 months, divided into two sub-periods of 8 months for the first sub-period and 14 months for the second sub-period.

5.4. Breaks dates – political and/or terrorist attacks

The results of the break dates and their corresponding potential events are reported below in Table 6. In particular, five breaks have been identified corresponding to October 2001, December 2003, January 2011, September 2011, May 2015, and June 2016. As shown in Table 6, all five determined breaks correspond to major political and/or terrorists shocks that have negatively affected the Tunisian tourism activity.

These shocks are detailed as follows:

Table 6
Breaks dates and major political events and/or terrorist attacks.

Break date	Political events and/or terrorist attacks
October 2001	September 2001 terrorist attacks in NewYork.
December 2003	End of the 09/11 and Djerba 05/2002 terrorist attack.
January 2011	Jasmine revolution, January 2011.
September 2011	The end of the effect of Jasmine revolution, January 2011 shock.
May 2015	Bardo National Museum and Sousse Attacks of March and May 2015.
June 2016	The end of the effect of the Bardo National Museum and Sousse Attacks

1. The first two break dates, October 2001 and December 2003, are associated with the beginning and ending of the first sub-period of regime 2. The first break of October 2001 corresponds to the September 11 attack (2001). This international shock seems to have had a significant impact on the number of tourist arrivals in Tunisia. However, as this break date fall into the intermediate regime (regime 2), then one can conclude that the effects of international shocks on the Tunisian tourism activity are less severe compared to the local shocks (political and terrorists attacks) that characterize regime 3. The duration of the October 2001 break was extended in terms of duration by the Djerba terrorist attack of May 2002. The second break of December 2003 is just the break date corresponding to the end of the October 2001 shock. In terms of duration, the effects of this break persisted for 26 months.
2. The third break date corresponds to the Tunisian Jasmine revolution of January 2011. This shock seems to have the most severe effects on the Tunisian tourism activity compared to all the other shocks (see Fig. 3). This shock has the lowest duration, lasting for only 8 months. This can be explained by the fact that this shock happened in the low season of tourism activity. Moreover, this shock seems to have had a negative short effect due to the absence of security; however, it had a positive impact in the medium-long run, mainly once the security in the country was restored. This can be explained by the fact that tourists are generally interested in visiting countries with special "achievements", such as countries where people are revolting in favor of democracy. The break of September 2011 corresponds to the end of the impact of the Jasmine revolution shock on the tourism activity.
3. Finally, the last two break dates of May 2015 and June 2016 correspond to the Bardo National Museum terrorist attack on March 18, 2015, which was followed 3 months later on June 26, 2015 by the terrorist attack against two hotels at Port El Kantaoui, Sousse, a tourist resort. The duration of this sub-period of regime 3 is 14 months (1 year and 2 months). The largest effects in terms of shock duration, compared to the Jasmine revolution shock, can be explained by the difference in nature of these two breaks. For instance, whereas the Jasmine revolution can be considered as a political shock, the March–June 2015 shocks are considered terrorist attack shocks. Moreover, this difference in terms of duration can be explained by the increased number of terrorist attacks during 2015. These attacks can be divided into two groups: (1) attacks against a

touristic location, which directly affect tourist arrivals, such as the two shocks considered and discussed previously (Bardo and Sousse attacks), and (2) attacks against the Tunisian army and security forces, which do not directly affect the number of tourist arrivals.

5.5. Results robustness checking

This section is devoted to assessing the robustness of the empirical results to (1) the method of deseasonalization and (2) the proxy of tourism activity employed. As a second method of deseasonalization, we propose the use of the ×12-ARIMA technique and as a second proxy of tourism activity, we propose the use of the number of overnights stays.

5.5.1. Robustness to deseasonalization method

As mentioned in subsection 2.2., the ×12-ARIMA technique will be used to examine the robustness of our results to different methods of deseasonalization. The results of using ×12-ARIMA as an alternative method of deseasonalization are reported in the supplementary document. Overall, the results regarding the unit root tests, long memory tests, and Shimotsu (2006a) tests are similar to those obtained when the TRAMO/SEATS technique is used to deseasonalize the tourist arrival series. The specification of the selected Markov switching model is also similar to that of the adjusted number of the tourist arrival series via the TRAMO/SEATS technique. The only important difference is that ×12-ARIMA failed to detect the break of September 2001. This can be explained by the fact that the TRAMO/SEATS technique performs better for a large sample size compared to ×12-ARIMA.

However, despite these differences, the results regarding the post-revolution shocks and their duration are the same as those detected using the TRAMO/SEATS technique.

5.5.2. Robustness to second proxy of tourism activity

The robustness of the empirical result is also examined by using the number of overnight stays as a second proxy of tourism activity. An important difference compared to the tourist arrival series is that this new proxy not only accounts for international overnight stays but also takes into consideration the overnight stays by local residents.

The same results as in sections 3 and 4 above are reported for the number of overnights stays in the supplementary document and for the two methods of deseasonalization. The results of the unit root tests with structural breaks do not show any significant differences compared to the results discussed above for the number of tourist arrivals. The results show evidence of stationarity for the monthly number of hotel rooms reserved when using unit root tests accounting for structural breaks. The date of the breaks are, overall, similar to those obtained in the case of the number of arrivals. Regarding the results of testing for long memory behavior, there is strong evidence for long memory behavior. However, when testing for true versus spurious long memory, the results show that the null hypothesis of true long memory is rejected when splitting the entire sample into 5 or 6 subsamples for the two values of the truncation parameter: $m = 20$ and $m = 40$. In line with the results of the unit root tests with structural breaks, which show evidence of stationarity with five breaks, the results of the splitting sample test of Shimotsu (2006a) confirm the evidence of short memory with structural breaks.

Regarding the results of the estimation of the Markov switching autoregressive model, the results show that the number of overnight stays is characterized by three-state Markov switching in both the intercept, trend, and variance coefficients. In addition, the results related to the dates of breaks confirm those obtained for the case of the monthly number of tourist arrivals, especially for the post-revolution period. However, the period before the Jasmine revolution is slightly different from that obtained for the number of tourist arrivals, especially in terms of the number of breaks, which is higher when using the TRAMO/SEATS method compared to the ×12-ARIMA technique.

6. Conclusion

This paper examines the effect of terrorist attacks and political instability on tourism activity in Tunisia. In particular, it investigates the magnitude of the effects of the Jasmine revolution and recent terrorist attacks on the number of tourist arrivals and number of overnights stays. The preliminary results show that the data seem to be characterized by four statistical properties: seasonality, unit root, structural breaks, and long memory. As a first step, to examine these statistical properties in detail, we use the unit root tests with structural breaks of Charfeddine and Guégan (2011), the modified R/S and V/S non-parametric tests of long memory, and the estimated values of the fractional long memory parameter d obtained by using the GPH, GSP, LW, ELW, and 2SFELW estimation methods. We test for true versus spurious long memory behavior by using the splitting test of Shimotsu (2006a). In the second step, once the evidence for changing in regimes is validated, we estimate a Markov switching model with a Markov change in the intercepts, trends, and variances for the number of tourist arrivals and the number of nights stayed. The results of the selected model are used to date exactly the breaks and to inspect the effects of the tourist attacks and political instability on tourism activity.

The main contributions of this study can be summarized in the following three points. First, whereas previous studies focused on the two possible extreme cases of transitory versus permanent impacts of terrorists and political violence on tourism activity, this study adds to the literature on the persistence of shocks on tourism demand by examining the intermediate case where political and terrorist attacks have long-lasting effects. Second, this study allows us to differentiate empirically the effects of terrorist shocks and political violence shocks in terms of magnitude and duration. We find evidence of four significant shocks that occurred after the end of the year 2010, compared to only one break before that date. Our results reveal that the effect of terrorist attack shocks on tourism activity is more severe than that of the Jasmine revolution. We also detected that, in terms of time duration, terrorist attack shocks have a more lasting effect (1 year and 2 months) compared to the Jasmine revolution shock (8 months). Third, we distinguish between internal and external shocks. Our results suggest that, for the case of Tunisia, internal shocks have the highest impact on tourism activity, whereas external shocks, including the terrorist attacks of September 11 and the global financial crisis of 2008, which fall into the second regime, have only a moderate impact. This latter result can be explained by the type and nature of the tourism sector in Tunisia, which is known as a low-cost destination.

Finally, this study proposes and discusses several marketing, economic, and security policies that can be implemented by Tunisian policymakers to better respond to all shocks that can affect the tourism industry in Tunisia.

7. Policy implications

Our empirical findings have several important policy implications in how to attenuate and reduce the negative impacts of political and terrorist attacks on Tunisian tourism activity. The results obtained from the determination of the true DGP of the number of tourist arrivals and the estimation of the appropriate Markov switching model suggest that the Tunisian tourism decision-makers from the government and private tourism managers should choose with caution the timing of their response depending upon the shocks' occurrence and the estimated impact. Indeed, determining factors affecting tourism demand, such as political instability and terrorist upheavals, and estimating their time path impact are very helpful for policy decision-makers when drawing and designing effective strategies to restore the tourism activity. Consequently, the Tunisian government should put more importance on national security and address terrorist attacks and the media sector with more professionalism.

7.1. Security policy

Our empirical findings show that terrorist attacks have a long duration compared to other types of shocks. This is mainly because many countries, including Great Britain, Belgium, the Netherlands, Sweden, and Denmark, prohibited travelling to Tunisia after the terrorist attacks of June 2015. Therefore, we believe that Tunisian authorities must work closely with the diplomatic missions of the European countries in the field of intelligence and the fight against terrorism. In addition, Tunisian diplomatic missions abroad must have a policy of economic communication of the image of Tunisia to different host countries to reassure foreign partners in matters of security. We believe that the improvement of inside security and the level of cooperation and communication with foreign governments may help to attenuate the impact of shocks on tourism activity.

7.2. Marketing policy

Generally, the media tends to exaggerate the virulence of terrorist events, negatively altering the destination's image, which can engender a decrease in tourist arrivals (Liu & Pratt, 2017). In terms of policy implications, decision makers in the Tunisian tourism industry need to reassure foreign tour operators and promote marketing initiatives and media policy to recover the positive image of the country because tourists may feel various levels of risk aversion to terrorist events.

The marketing policy must cover both the short and long terms. In the short term, the national tourism office in cooperation with tour operators must develop an anti-crisis communication policy to improve the image of Tunisia as an excellent tourism destination. Some international communication agencies established in the host countries must be involved in foreign media to temper the ardor of terrorist attacks and preserve the image of Tunisia as a safe country. In the long term, tourist operators in Tunisia must develop a commercial strategy aimed at extending the markets and reducing the risks of an over-dependence of tourist arrivals from the traditional Western markets by developing new opportunities from Eastern Europe and Asia (Czech Republic, Russia, Ukraine, China, etc.). Another possibility would be to promote Muslim-oriented tourism and develop in some regions such as Djerba, for example, new products closer to Muslim religious sensibilities.

7.3. Monetary policy

Tourists are generally risk averse to terrorist events. In such incidents, the Central Bank should adopt a more flexible exchange rate regime in the short term to reduce such risk aversion. The appreciation of foreign currencies vis-à-vis the Tunisian dinar should encourage some tourists less affected by security menaces to pursue their visit to affected destinations. This cyclical flexibility could reduce the trade deficit. Note that the Algerian market, which remains very faithful to Tunisia as a destination, generated nearly 1.5 million tourist admissions in 2015. Thanks to their extra hotel spending, they have played an important role in regional development dynamics, becoming the first tourist clientele in Tunisia. A Maghreb monetary union must start with Tunisia's Algerian neighbors, would could boost Algerian tourist arrivals in Tunisia. Moreover, Tunisia must reduce its monetary dependency on the strength of the euro by developing a partnership with the Chinese market and adopting its currency as a foreign currency to diversify Tunisia's trade policy.

7.4. Budgetary policy

There is also a need to implement a countercyclical budgetary policy that takes the volatility of foreign exchange earnings coming from the tourism industry into account following internal shocks and sets up an allocation process for recovery campaign funding. The creation of a fund to support tourism services would make it possible to reduce the negative impact of a terrorist event on tourism activity following the transitory decline of arrivals of tourists in Tunisia and its social consequences. This fund should be financed during the period of rising tourism receipts from exceptional tourist seasons to act as a "shock absorber" during transitional periods of crisis following the advent of political instability or terrorist attacks because the recovery is likely to be slow afterwards. This fund can have two goals. The first is a social policy aiming to reduce the severity of the temporary job losses in the tourism industry after terrorist events. The second is serving as an advertising operation, updating overseas communication policy according to markets, to restore the value of the Tunisian offer and the image of the destination.

Despite the important results found in this study and their policy implications discussed in the next section, the current study has some limitations that can be explored in future research. These limits include, for example, the short period of study in terms of the number of observations and the non-exploration of the performance of the models examined in terms of out-of-sample forecasting and in determining the true nature of the observed long memory behavior. As suggested above, these points can be explored in future research.

Appendix

1. Unit root tests with structural breaks of Carrion-i-Silvestre et al. (2009a).

The model considered by Carrion-i-Silvestre et al. (2009a) is the following,

$$y_t = d_t + \varepsilon_t \tag{A1}$$

$$\varepsilon_t = \alpha\, \varepsilon_t + \nu_t \quad t = 0, \ldots, T \tag{A2}$$

where y_t is a time series, $\{\varepsilon_t\}$ is the error term with mean zero. ε_0 is supposed to be equal to 0. The disturbance ν_t is defined as $\nu_t = \sum_{i=0}^{\infty} \gamma_i \eta_{t-i}$, with $\sum_{i=0}^{\infty} i|\gamma_i| < \infty$ and $\{\eta_t\}$ as a martingale difference sequence adapted to the filtration $F_t = \sigma - field\{\eta_{t-i};\, i \geq 0\}$. The long and short run variances are defined as $\sigma^2 = \sigma_\eta^2 \gamma(1)^2$ and $\sigma_\eta^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E(\eta_t^2)$, respectively.

The component d_t in (1) is given by the following,

$$d_t = z_t'(\lambda)\psi, \tag{A3}$$

where,

$$z_t'(\lambda) = [z_t'(T_0), z_t'(T_1), \ldots, z_t'(T_m)] \text{ and } \psi = (\psi_0', \psi_1', \ldots, \psi_m')' \tag{A4}$$

The deterministic component $z_t'(T_j)$ and the coefficient ψ define three principal models largely explored and used in the empirical literature. These models correspond to the crash (level shift), the slope change and the mixed change models.

In this paper, we focused our analysis in the crash and mixed change models (see Perron, 1989).[4]

[4] See also Zivot and Andrews (1992), Ng and Perron (1995) and Lee and Strazicich (2003).

For the level shift model known as the crash model, the deterministic component $z_t'(T_j)$

$$z_t'(T_j) = DU_t(T_j) \tag{A5}$$

for the mixed change model,

$$z_t'(T_j) = (DU_t(T_j),\ DT_t^*(T_j))'. \tag{A6}$$

For $j = 0$, $z_t'(T_0) \equiv z_t(0) = (1, t)'$ and $\psi_0 = (\mu_0, \beta_0)'$. For $1 \le j \le m$, $\psi_j = \mu_j$ in the crash model and $\psi_j = (\mu_j, \beta_j)'$ in the mixed change model. $DU_t(T_j) = 1$ and $DT_t^*(T_j) = (t - T_j)$ for $t > T_j$ and 0 otherwise. $T_j = [T\lambda_j]$, which denotes the j-th break date, with [.] defining the integer part, and $\lambda_j \equiv T_j/T \in (0,1)$ as the break fraction parameter. The authors use the sum of squared residuals (SSR) of the GLS-detrended model to estimate the break dates, the authors used the global minimization of the.

The four tests that we propose to use in this study are the counterpart tests of the Eliot et al. (1996) for the case of unit root tests without breaks. The tests are the $MZ_\alpha^{GLS}(\lambda)$, $MSB^{GLS}(\lambda)$, $MZ_t^{GLS}(\lambda)$ and $MP_T^{GLS}(\lambda)$ tests where λ is as defined above.

The limit distribution and the critical values of all these tests are obtained by simulation, see Carrion-i-Silvestre et al. (2009a) paper for more details.

2. *Shimotsu (2006a) test of true versus long range dependence*

The Shimotsu (2006a) test consists of splitting the tourist arrivals time series into b subsamples and in comparing the estimated long memory parameter d of the entire sample to the estimated fractional long memory parameter of each subsample. The idea of this test is based on the following assumption: If the observed long memory behavior is a true behavior, then the estimated fractional long memory parameter of d for the full sample should not be statistically different from those estimated from the subsamples (see Charfeddine, 2016; Abuzayed et al., 2018; and; Charfeddine & Maouchi, 2018).

The null hypothesis of true long memory $I(d)$ is,

$$H_0\text{:True long memory}(H_0 : d = d^{(1)} = \ldots = d^{(b)}) \tag{A7}$$

The alternative hypothesis corresponds to,

$$H_1\text{:Short memory affected by breaks} \tag{A8}$$

where $d^{(i)}$ for $i \in \{1,2,\ldots,b\}$ is the true value of the fractional long memory parameter from the ith subsample and d is the true value for the full sample.

The test statistic proposed by Shimotsu (2006a) is given by,

$$W_c = 4m\left(\frac{c_{m/b}}{m/b}\right) A\ \hat{d}_b\ (A\Omega A')^{-1}(A\hat{d}_b)' \tag{A9}$$

where,

$$\hat{d}_b = \begin{pmatrix} \hat{d} - d \\ \hat{d}^{(1)} - d \\ \vdots \\ \hat{d}^{(b)} - d \end{pmatrix}, \quad A = \begin{pmatrix} 1 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & -1 \end{pmatrix} \quad \Omega = \begin{pmatrix} 1 & \tau_b' \\ \tau_b & bI_b \end{pmatrix},$$

where I_b is a $(b \times b)$ identity matrix and τ_b is a $(b \times 1)$ vector of ones. m is the number of the periodogram ordinates used in the objective function. c_m is a number given by,

$$c_m = \sum_{j=1}^{m} v_j^2, \quad v_j = \log\lambda_j - \frac{1}{m}\sum_{j=1}^{m}\log\lambda_j = \log j - \frac{1}{m}\sum_{j=1}^{m}\log j$$

Shimotsu (2006a) shows that the limiting distribution of the splitting test W_c is the chi-squared limiting distribution with $b - 1$ degrees of freedom.

Note: The critical values for the W_c statistic for the Shimotsu (2006) is $\chi^2(b-1)$ where b is the number of subsamples. and $\chi^2(4) = 9.49$ and $\chi^2(5) = 11.070$ at the 5% level of significance and equal to $\chi^2(4) = 13.277$ and $\chi^2(5) = 15.086$ at the 5% level of significance.

Author contribution

Dr. Lanouar Charfeddine contribution to this paper includes writing the abstract and performing all the two sections of “Data and preliminary analysis” and “a Markov Switching model for the number of tourist arrivals”. The contribution includes also the participation in writing the introduction, literature review, the tourism sector in Tunisia and conclusion sections as well as the discussion and validation of the policy implication section.

Prof. Mohamed Goaied contribution to this paper includes participation in writing the introduction, literature review, the tourism sector in Tunisia, and conclusion sections as well as the data collection and all the section of policy implication. The contribution includes also the discussion and validation of the empirical analysis.

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