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PERSISTENCE, LONG MEMORY AND SEASONALITY IN KENYAN TOURISM SERIES

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ABSTRACT

This article investigates tourism in Kenya by looking at the degree of persistence in the total number of arrivals and departures for the time period from 1975Q1 to 2011Q4. We use long range dependence techniques and given the quarterly nature of the series examined, seasonality is also taken into account. The results indicate that the tourism sector in Kenya is especially sensitive to political shocks. This is particularly exemplified by the shocks in 1992Q4 and 2008Q1 that were associated with crucial election periods in Kenya. Our results, however, show that shocks are expected to be transitory, disappearing relatively fast.

Keywords: Total arrivals; total departures, Kenya; persistence

JEL classification: C22; L83; O55

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1. Introduction

Kenyan tourism sector remains critical in terms of its contribution to economic growth and Gross Domestic Product. It is to date the most important export service for the Kenyan economy and one of the most vibrant tourism sectors in Sub-Saharan Africa. In 2011 earnings from the tourist sector rose to Ksh 97.9 billion from Ksh 73.7 billion in 2010. The Hotels and Restaurant sector recorded growth of 5% in 2011 compared to 4.2% in 2010. This growth was mainly due to increased international arrivals, conference activities and the high number of tourist arrivals in the year 2011. Earnings from the tourist sector were also boosted by a depreciation of the Kenya shilling in the second half of 2011 (Kenya National Bureau of Statistics, 2012). The Kenyan tourism sector is, however, very sensitive to fluctuations in Kenya's international image. For example, following the post-election violence in 2008 there was a substantial decline in the tourism influx to Kenya. Tourism revenues were also been adversely affected in 2012 following pre-election violence in August 2012 that saw several travel advisories being issued against Kenya. Political developments in 2013, a period leading to the general elections will be a crucial determinant of economic growth and will have an important impact on tourist arrivals. Electoral shocks in the past have also always resulted in a decline in tourist arrivals in Kenya owing to the perception of Kenya as a more risky destination during election periods.

Based on the above comments, it is interesting to study whether negative shocks produced by political instability such as the post-election violence in 2008 are transitory or not, and whether strong policies should be implemented to recover or even to increase the number of arrivals in Kenya. There is therefore a need for proposing a new modelling approach for the total number of international arrivals in Kenya using fractional integration. This methodology, though widely used in other more developed tourism destinations, has never been carried out in Kenya and should provide some interesting policy insights.

The paper deals with the analysis of the total number of international arrivals and departures in Kenya over the period 1975 to 2011, quarterly. The analysis is carried out by examining the degree of persistence and the seasonality. The degree of persistence helps us to know the nature and the effects of the shocks in the tourism series. Also seasonality is an important feature that is usually present in many quarterly and monthly series. According to Song and Li (2008), seasonality is a notable characteristic of tourism demand and cannot be ignored in the modelling process when monthly or quarterly data are used.

The main contribution of the paper is the following. To our knowledge this is the first study on the tourism demand for the Kenyan economy using a long memory approach which also takes seasonality into account. Previous papers on tourism demand in Africa are focused on a global view of Africa, Zimbabwe, South Africa and Kenya but use other empirical approaches (see, for example, Burger et al., 2001; Christie and Crompton, 2001; Kester, 2003; Naudé and Saayman, 2005; Saayman and Saayman, 2010; Muchapondwa and Pimhidzai, 2011; Kuto and Groves, 2004 and Kiarie, 2008 among others). We propose an innovative empirical approach for quarterly data based on long range dependence techniques, taking into account the existence of possible structural breaks. Previously, some other papers have also used a similar empirical approach to analyse the tourism demand for the US and Spain (see, for example, Cunado et al., 2008 and Gil-Alana et al., 2004 among many others).

The rest of the paper is structured as follows. Section 2 briefly summarizes the literature review on tourism demand modeling and forecasting. Section 3 briefly describes the methodology employed in the paper. Section 4 describes the data and presents the main results of the paper, while Section 5 contains some concluding comments and extensions.

2. Literature review on tourism demand

Previous economic literature on tourism demand modelling and forecasting is extensive. For example, according to Li et al. (2005) 420 studies on tourism demand modelling and forecasting were published during the period 1960 – 2002.

The literature proposed alternative approaches to study tourism demand.[1] For example, there are papers based on error correction models (see, for example, Kulendran and Wilson, 2000; Song and Witt, 2000; Lim and McAleer, 2001 Kulendran and Witt, 2003); others use vector autoregressive models (Shan and Wilson, 2001; Witt et al., 2004 and Song and Turner, 2006); and AutoRegressive Distributed Lag (ARDL) models (Song et al., 2003a,b). Alternative quantitative approaches such as artificial neural network methods (Burger et al., 2001; Cho, 2003 and Kon and Turner, 2005); fuzzy time series methods (Wang, 2004) and genetic algorithms (Burger et al., 2001; Hernández-López, 2004 and Pai et al., 2006) have also been recently used in the literature on the topic.

As mentioned in the preceding section, we focus on the total number of arrivals and departures in Kenya. Previous papers studying tourism demand in Africa are Burger et al. (2001), Naudé and Saayman (2005), Saayman and Saayman (2010) and Muchapondwa and Pimhidzai (2011) among many others. For example, Burger et al. (2001) compare a variety of time series forecasting methods (i.e., ARIMA, neural networks and single-exponential smoothing among others) to predict US tourism demand to Durban, South Africa using data from 1992 to 1998. Their results suggest

[1] An excellent review on tourism demand modeling and forecasting can be found in Song and Li (2008).

that the best forecast model is neural networks. Alternatively, Naudé and Saayman (2005) uses both cross-section and panel data to identify the determinants of tourism arrivals in 43 African economies during the period 1996 – 2000. Their results show that political stability, tourism infrastructure, marketing and information, and the level of development at the destination are key determinants of travel to Africa. In another paper, Saayman and Saayman (2010) use time series models to forecast tourist arrivals in South Africa using monthly data from 1994 to 2006. The most accurate prediction is based on a seasonal ARIMA model. Recently, Muchapondwa and Pimhidzai (2011) use the autoregressive distributed lag model to model tourism demand for Zimbabwe using data from 1998 to 2005. The results show that taste formation, transport costs, and changes in global income have a significant impact on international tourism demand. In this paper, we follow a different time series approach and we model the total number of international arrivals and departures in Kenya by means of fractional integration procedures. Others papers that also focused on tourism data using fractional integration are Cunado et al. (2008), Gil-Alana et al. (2004) and Gil-Alana (2005, 2008) among others.

Several papers have considered tourism demand in Kenya but none have adopted a long memory and a seasonality perspective. Okello et al. (2012) consider the factors influencing domestic tourism for urban and semi-urban populations around Nairobi National Park in Kenya. They found that the level of education influenced the likelihood of the community visiting the park and appreciating its conservation contribution. Even though the lack of free time, lack of interest in wildlife, or the idea that protected areas in Kenya were meant for foreign tourists, were not obstacles to the local community visiting the parks, they noted that key constraints were the lack of sufficient disposable income, the high cost of food and hospitality services inside the park for local communities, and poor marketing of parks especially targeting local Kenyans hindered high visitation rates for local Kenyans to protected areas. Kiarie (2008) estimates inbound tourism demand for Kenya using a gravity approach. The study is aimed at estimating inbound tourism for Kenya with respect to the UK, Germany, Italy, France, Switzerland, US, Canada, Japan, and India. The general method of moments was applied to a dynamic panel data for the period 1987 - 2006. The results reveal that income per capita in tourist generating countries, habit persistence and a word-of-mouth effect, distance, tourism prices, visa fee charges and security are key determinants of tourist demand in Kenya. On the other hand, per capita income in Kenya was not found to be statistically significant in the study. Kuto and Groves (2004) consider the impact of terrorism on tourism in Kenya. Terrorism in Kenya has adversely affected the tourism industry with many hotels almost collapsing and thousands of Kenyans losing their jobs. The paper also attempts to come up with a crisis management plan. Sindiga (1996) considers the demand generated by domestic tourism in Kenya. He finds that some Kenyans have begun to take advantage of promotional incentives although this appears to be at an incipient stage. The paper argues that the income of Kenyan workers is too low to pay for tourism even at the concessionary rates offered by hotels each year when international tourism is off-season. He contends that to encourage domestic tourism, certain structural adjustments leading to tourism product diversification and spatial de-concentration of facilities will cater for a broader cross section of people.

Several papers have considered the impact of tourism in Kenya. For example Kibara et al. (2012) examine the dynamic relationship between tourism sector development and economic growth using annual time series data from Kenya. The study uses an ARDL bounds testing approach to examine these linkages and incorporates trade as an intermittent variable between tourism development and growth in a multivariate context. Their results show that there is uni-directional causality from tourism development to growth irrespective of whether the causality is estimated in the short run or long run. Mshenga (2009) focuses on the impact of tourism on the development of small and medium enterprises. From her analysis, small and medium enterprises were found to have the most potential in the areas of hotel food supply, child care services, room cleaning services, garbage collection, handicrafts and souvenirs, security services, maintenance and repair services. The results underscore the role of tourism in the growth of small businesses, in improving rural livelihoods and bringing about poverty alleviation. Many papers on tourism in Kenya focus on how tourism demand can be enhanced in Kenya though appropriate promotional activities. For example, Okech (2011) focuses on promoting sustainable festival events tourism using the case study of Lamu. She argues that cultural festivals have emerged as an instrument for tourism development, tourism seasonality expansion, city image improvement and boosting economies. Therefore, the implications would be to invest in festivals development and community engagement and present the tourist with authentic experiences. Akama (2002) uses the case study of Kenya to analyse the role of government in the development of tourism in the Third World. Usually, government involvement in the development of tourism reflects on the uniqueness and peculiarity of the tourism industry. He argues that the Kenya Government has, over the years, played a crucial role in the development of the country's tourism industry. The study also examines the underlying factors responsible for the downturns in Kenyan tourism industry and how they relate to the role of government in the development of tourism. However, no paper on tourism in Kenya to date considers persistence, long memory and seasonality in a unified treatment.

3. Methodology

We use techniques based on the concept of long range dependence (LRD) or long memory processes. There are two possible definitions of long memory. Given a covariance stationary process $\{x_t, t = 0, \pm 1, \ldots\}$, with autocovariance function $E(x_t - Ex_t)(x_{t-j} - Ex_t) = \gamma_j$, according to McLeod and Hipel (1978), x_t displays LRD if

$$\lim_{T \to \infty} \sum_{j=-T}^{T} \left|\gamma_j\right| \tag{1}$$

is infinite. An alternative definition, based on the frequency domain, is the following. Suppose that x_t has an absolutely continuous spectral distribution function, implying that it has a spectral density function, denoted by $f(\lambda)$, and defined as

$$f(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j \cos \lambda j, \qquad -\pi < \lambda \leq \pi. \tag{2}$$

Then, x_t displays the property of long memory if the spectral density function has a pole at some frequency λ in the interval $[0, \pi)$, i.e.,

$$f(\lambda) \to \infty, \quad \text{as} \quad \lambda \to \lambda^*, \qquad \lambda^* \in [0, \pi).$$

Most of the empirical literature in the last twenty years has focused on the case where the singularity or pole in the spectrum occurs at the 0 frequency, i.e.,

$$f(\lambda) \to \infty, \quad as \quad \lambda \to 0^+.$$

This is the standard case of I(d) models of the form:

$$(1 - L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{3}$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined for our purposes as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency.

Given the parameterization in (3) we can distinguish several cases depending on the value of d. Thus, if d = 0, $x_t = u_t$, x_t is said to be "short memory" or I(0), and if the observations are autocorrelated (e.g. AR) they are of a "weak" form, in the sense that the values in the autocorrelations are decaying exponentially fast; if $d > 0$, x_t is said to be "long memory", so named because of the strong association between observations which are very distant in time. Here, if d belongs to the interval (0, 0.5) x_t is still covariance stationary, while $d \geq 0.5$ implies nonstationarity. Finally, if $d < 1$, the series is mean reverting in the sense that the effect of the shocks disappears in the long run, contrary to what happens if $d \geq 1$ with shocks persisting forever.

There exist several methods for estimating and testing the fractional differencing parameter d. Some of them are parametric while others are semiparametric and can be specified in the time or in the frequency domain. In this paper, we use a testing procedure, which is based on the Lagrange Multiplier (LM) principle and that uses the Whittle function in the frequency domain. It tests the null hypothesis:

$$H_o: \; d \; = \; d_o, \qquad (4)$$

for any real value d_o, in a model given by the equation (3), where x_t can be the errors in a regression model of the form:

$$y_t \; = \; \beta^T z_t \; + \; x_t, \qquad t \; = \; 1, 2, \ldots, \qquad (5)$$

where y_t is the observed time series, β is a (kx1) vector of unknown coefficients and z_t is a set of deterministic terms that might include an intercept (i.e., $z_t = 1$), an intercept with a linear time trend ($z_t = (1, t)^T$), or any other type of deterministic processes. Robinson (1994) showed that, under certain very mild regularity conditions, the LM-based statistic[2] $(\hat{r})$:

$$\hat{r} \; \rightarrow_{dtb} \; N(0, 1) \qquad \text{as} \qquad T \; \rightarrow \; \infty,$$

[2] The specific form of the statistic is presented in Appendix A.

where " $\rightarrow_{dtb}$ " stands for convergence in distribution, and this limit behaviour holds independently of the regressors z_t used in (5) and the specific model for the I(0) disturbances u_t in (3).

As in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives have the same null and limit theory as the LM test of Robinson (1994). Lobato and Velasco (2007) essentially employed such a Wald testing procedure, though it requires a consistent estimate of d; therefore the LM test of Robinson (1994) seems computationally more attractive.

4. Empirical results

We used quarterly data for the total number of international departures and arrivals in Kenya from 1971Q1 to 2011Q4 yielding 148 observations. All data are obtained from various issues of the Economic Survey produced by the Kenya National Bureau of Statistics.

[Insert Figure 1 about here]

Figure 1 displays plots of the two original series. We observe that the values increase across the sample, with two negative shocks occurring at 1992Q4 and 2008Q1. Both of these negative shocks correspond to election periods in Kenya. The first shock was associated with the election accompanying the advent of multiparty politics in 1992. This election period marked a major transition in Kenya from one party to multi-party rule and was associated with considerable uncertainty. The Cold War had just ended and a wind of change was blowing across many African states including Kenya informed by changing geo-political interests in a Post Cold War World. The year 1992 had been a year of major agitation for constitutional reforms with a demand that elections take place under a new constitution. The second shock in the first quarter of 2008 was associated with the ethnic violence that followed the disputed election results in December 2007. The series also present a clear seasonal pattern that is more visible in the correlograms displayed in Figure 2. The periodograms of the two series are displayed in Figure 3 and show the highest values at the smallest frequency, which is consistent with long memory specifications as explained in Section 3. This is also reaffirmed in Figure 4, showing the periodograms of the first differenced series, which show values close to zero at the zero frequency implying then overdifferentiation.[3]

[Insert Figures 1 to 4 about here]

We consider the following model,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t, \qquad t \;=\; 1, 2, \tag{6}$$

$$(1 - L)^d \, x_t \;=\; u_t, \qquad t \;=\; 1, 2, \ldots, \tag{7}$$

and given the quarterly nature of the series examined, we assume that u_t in (7) follows a seasonal (quarterly) AR(1) process of form:

$$u_t \;=\; \rho u_{t-4} + \;\varepsilon_t, \qquad t \;=\; 1, 2, \ldots, \tag{8}$$

where ε_t is a white noise process.[4]

We estimate the fractional differencing parameter d for the three standard cases examined in the literature, i.e., the case of no regressors (i.e., $\alpha = \beta = 0$ *a priori* in equation (6)), an intercept (α unknown, and $\beta = 0$ *a priori*), and an intercept with a linear time trend (α and β unknown). Together with the estimate of the fractional differencing parameter, we also present the 95% confidence band of the non-rejection values of d, using Robinson's (1994) parametric tests. The results are displayed in Table 1.

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[3] If a series is overdifferenced, $f(\lambda) \rightarrow 0$ as $\lambda \rightarrow 0^+$.

[4] Higher seasonal AR orders were also considered leading to very similar results to those reported in the paper.

[Insert Table 1 about here]

As expected, the results indicate that the value of d is in all cases in the interval (0, 1) implying long memory (d > 0) and mean reverting (d < 1) behaviour. We notice that the values are slightly higher for the departures series and the time trend seems to be required in the two series. Table 2 displays the estimated coefficients for each series.

[Insert Table 2 and Figure 5 about here]

We see that for the arrivals, the estimate of the fractional differencing parameter is 0.420 while that for the departures is 0.443. Thus, in both cases we are close to the boundary line between stationary and nonstationary behaviour (d = 0.5). The slope coefficient is slightly higher for the arrivals, and the same happens with the seasonal AR coefficient, being equal to 0.554 for arrivals and 0.481 for departures. Figure 5 displays the estimated time trends in the two cases.

In the final part of the manuscript we investigate the potential presence of breaks in the data. For this purpose we use the methodology devised by Gil-Alana (2008) for estimating fractional differencing parameters and deterministic terms in the context of structural breaks, with the number of breaks and the dates of the breaks being endogenously determined by the model. The model can be specified as follows:

$$y_t = \beta_i^T z_t + x_t; \quad (1 - L)^{d_i} x_t = u_t, \quad t = 1, \ldots, T_b^i, \quad i = 1, \ldots nb, \tag{9}$$

where nb is the number of breaks, y_t is the observed time series, the β_i's are the coefficients corresponding to the deterministic terms; the d_i's are the orders of integration for each sub-sample, and the T_b^i's correspond to the times of the unknown breaks. This method is briefly described in Appendix B. Note that given the difficulties in distinguishing between models with fractional orders of integration and those with broken deterministic trends (Diebold and Inoue, 2001; Granger and Hyung, 2004), it is important to consider estimation procedures that deal with fractional unit roots in the presence of broken deterministic terms.

[Insert Table 3 and Figure 6 about here]

Using the above approach in a model with an intercept and a linear time trend, the results indicate that there is evidence of a single break in the two series examined.[5] The estimated coefficients are displayed in Table 3. We see that the break date is found to be in the second quarter of 1983 in the two series. Before the break, the two series seem to be stationary I(0) and only an intercept is required to describe the deterministic part of the process. However, after the break the two series are I(d) with $d > 0$, implying long memory, and there is a significant trend in the two series. (See Figure 6).

5. Conclusions and discussion

In this paper we have examined the time series behaviour of the total number of departures and arrivals in Kenya for the time period 1975Q1 - 2011Q4. Analysis of the Kenyan tourism sector is crucial in terms of its contribution to the economic growth and the GDP in Kenya. The results based on total departures and arrivals suggest that the tourism sector is especially sensitive to political shocks. This is particularly exemplified by the shocks in 1992Q4 and 2008Q1 that were associated with crucial election periods in Kenya. Our results first show that there is a structural break at the beginning of the 80s, observing a linear deterministic trend during the last twenty years, which might be related with an increase in tourism opportunities in the country. At the same time, we also observe an increase in the degree of dependence across the sample, though the fact that the fractional differencing parameters are in the two

[5] The number of breaks was determined according to the AIC criterion. See the Appendix for this and other criteria.

subsamples which are strictly smaller than 1 indicates that the shocks are transitory, disappearing in the long run.

Appendix A: Robinson (1994) test statistic

The test statistic proposed by Robinson (1994) for testing H_o (4) in the model given by equations (5) and (3) is given by:

$$\hat{R} = \frac{T}{\hat{\sigma}^4} \hat{a}' \hat{A}^{-1} \hat{a},$$

where T is the sample size, and

$$\hat{a} = \frac{-2\pi}{T} \sum_j^* \psi(\lambda_j) g_u(\lambda_j; \hat{\tau})^{-1} I(\lambda_j); \qquad \hat{\sigma}^2 = \sigma^2(\hat{\tau}) = \frac{2\pi}{T} \sum_{j=1}^{T-1} g_u(\lambda_j; \hat{\tau})^{-1} I(\lambda_j),$$

$$\hat{A} = \frac{2}{T} \left(\sum_j^* \psi(\lambda_j) \psi(\lambda_j)' - \sum_j^* \psi(\lambda_j) \hat{\varepsilon}(\lambda_j)' \left(\sum_j^* \hat{\varepsilon}(\lambda_j) \hat{\varepsilon}(\lambda_j)' \right)^{-1} \sum_j^* \hat{\varepsilon}(\lambda_j) \psi(\lambda_j)' \right)$$

$$\psi(\lambda_j) = \log \left| 2 \sin \frac{\lambda_j}{2} \right|; \qquad \hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial \tau} \log g_u(\lambda_j; \hat{\tau});$$

with $\lambda_j = 2\pi j/T$, and the summation in * is over all frequencies which are bounded in the spectrum. $I(\lambda_j)$ is the periodogram of $\hat{u}_t = (1-L)^{d_o} y_t - \hat{\beta}' \bar{z}_t$, with

$$\hat{\beta} = \left(\sum_{t=1}^{T} \bar{z}_t \bar{z}_t' \right)^{-1} \sum_{t=1}^{T} \bar{z}_t (1-L)^{d_o} y_t;$$

$\bar{z}_t = (1-L)^{d_o} z_t$, evaluated at $\lambda_j = 2\pi j/T$ and $\hat{\tau} = \arg\min_{\tau \in T^*} \sigma^2(\tau)$, with T^* as a suitable subset of the R^q Euclidean space. Finally, the function g_u above is a known function coming from the spectral density of u_t:

$$f(\lambda) = \frac{\sigma^2}{2\pi} g_u(\lambda; \tau), \qquad -\pi < \lambda \leq \pi.$$

Note that these tests are purely parametric and, therefore, they require specific modelling assumptions about the short-memory specification of u_t. Thus, if u_t is white noise, $g_u \equiv 1$, and if u_t is an AR process of the form $\phi(L)u_t = \varepsilon_t$, $g_u = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of τ.

Appendix B: Gil-Alana's (2008) method for fractional integration with breaks

The model presented in (9) for the case of a single break can be expressed as:

$$(1-L)^{d_1} y_t \;=\; \beta_1 \tilde{z}_t(d_1) \;+\; u_t, \quad t \;=\; 1, \ldots, T_b,$$

$$(1-L)^{d_2} y_t \;=\; \beta_2 \tilde{z}_t(d_2) \;+\; u_t, \quad t \;=\; T_b+1, \ldots, T,$$

where $\tilde{z}_t(d_i) = (1-L)^{d_i} z_t$, i = 1, 2. The procedure is based on the least square principle. First we choose a grid for the values of the fractionally differencing parameters d_1 and d_2, for example, d_{io} = 0, 0.01, 0.02, …, 1, i = 1, 2. Then, for a given partition $\{T_b\}$ and given initial d_1, d_2-values, $(d_{1o}^{(1)}, d_{2o}^{(1)})$, we estimate the α's and the β's by minimizing the sum of squared residuals,

$$\min_{w.r.t.\{\alpha_1, \alpha_2, \beta_1, \beta_2\}} \sum_{t=1}^{T_b} \left[(1-L)^{d_{1o}^{(1)}} y_t - \beta_1 \tilde{z}_t(d_{1o}^{(1)})\right]^2 + \sum_{t=T_b+1}^{T} \left[(1-L)^{d_{2o}^{(1)}} y_t - \beta_2 \tilde{z}_t(d_{2o}^{(1)})\right]^2 .$$

Let $\hat{\beta}(T_b;\, d_{1o}^{(1)}, d_{2o}^{(1)})$ denote the resulting estimates for partition $\{T_b\}$ and initial values $d_{1o}^{(1)}$ and $d_{2o}^{(1)}$. Substituting these estimated values on the objective function, we have RSS(T_b; $d_{1o}^{(1)}$, $d_{2o}^{(1)}$), and minimizing this expression across all values of d_{1o} and d_{2o} in the grid we obtain $RSS(T_b) = \arg\min_{\{i,j\}} RSS(T_b; d_{1o}^{(i)}, d_{2o}^{(j)})$. Next, the estimated break date, $\hat{T}_k$, is such that $\hat{T}_k = \arg\min_{i=1,\ldots,m} RSS(T_i)$, where the minimization is taken over all partitions T_1, T_2, …, T_m, such that $T_i - T_{i-1} \geq |\varepsilon T|$. Then, the regression parameter estimates are the associated least-squares estimates of the estimated k-partition, i.e., $\hat{\beta}_i = \hat{\beta}_i(\{\hat{T}_k\})$, and their corresponding differencing parameters, $\hat{d}_i = \hat{d}_i(\{\hat{T}_k\})$, for i = 1 and 2.

The model can be extended to the case of multiple breaks. Thus, we can consider the model,

$$y_t = \alpha_j + \beta_j t + x_t; \ (1 - L)^{d_j} x_t = u_t, \quad t = T_{j-1}+1,...,T_j,$$

for j = 1, …, m+1, $T_0 = 0$ and $T_{m+1} = T$. Then, the parameter m is the number of changes. The break dates (T_1, …, T_m) are explicitly treated as unknown and for i = 1, …, m, we have $\lambda_i = T_i/T$, with $\lambda_1 < \ldots < \lambda_m < 1$. Following the same process as in the previous case, for each j-partition, {T_1, …T_j}, denoted {T_j}, the associated least-squares estimates of α_j, β_j and the d_j are obtained by minimizing the sum of squared residuals in the d_i-differenced models, i.e.,

$$\sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} (1 - L)^{d_i} (y_t - \alpha_i - \beta_i t)^2,$$

where $\hat{\alpha}_i(T_j)$, $\hat{\beta}_i(T_j)$ and $\hat{d}(T_j)$ denote the resulting estimates. Substituting them in the new objective function and denoting the sum of squared residuals as $RSS_T(T_1, \ldots, T_m)$, the estimated break dates $(\hat{T}_1, \hat{T}_2, ..., \hat{T}_m)$ are obtained by $\min_{(T_1, T_2, ..., T_m)} RSS_T(T_1, ..., T_m)$ where the minimization is again obtained over all partition (T_1, …, T_m).

Appendix C: Determining the number of breaks in Gil-Alana's (2008) procedure

The procedure developed by Gil-Alana (2008) requires the a priori determination of the number of breaks in the time series. Following standard procedures to select the number of breaks in the context of I(0) processes, Schwarz (1978) proposed the criterion: $SIC(m) = \ln[RSS_T(\hat{T}_1, ..., \hat{T}_m) / (T - m) + 2 p^* \ln(T)/T$, where p^* is the number of unknown parameters. The estimated number of break dates, $\hat{m}$, is then obtained by minimizing the above-mentioned criterion given M a fixed upper bound for m.

Other well-known criteria are the Bayesian criterion: $BIC(m) = \ln [RSS_T(T_1, \ldots, T_m)/T] + p^* \ln(T)/T$, and the $YIC(m) = \ln [RSS_T(T_1, \ldots, T_m)/T] + mC_T/T$, where C_T is any sequence satisfying $C_T T\text{-}2d/k \to \infty$ as $T \to \infty$ for some positive integer k.

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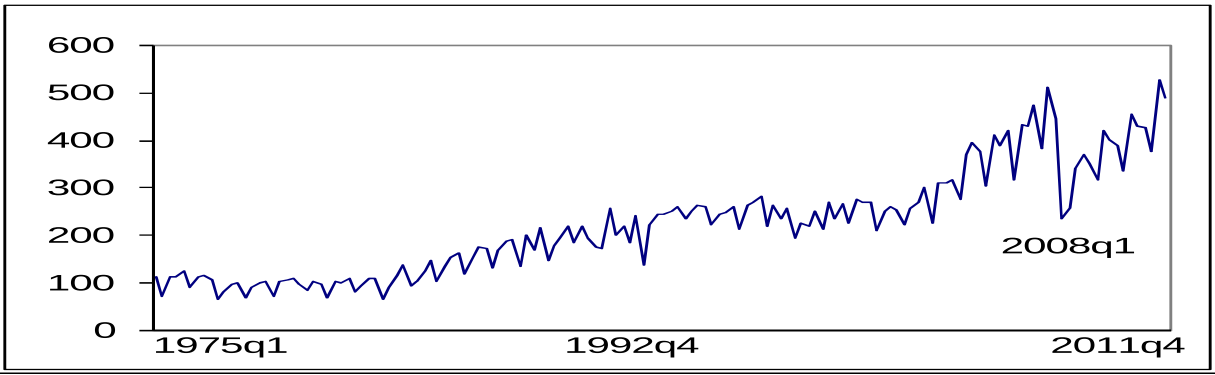
Figure 1: Original time series

i) Total arrivals



ii) Total departures

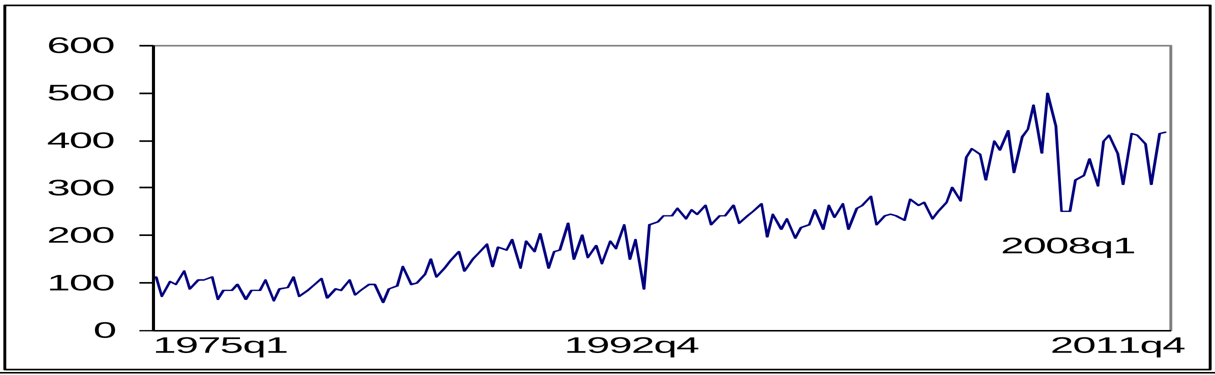
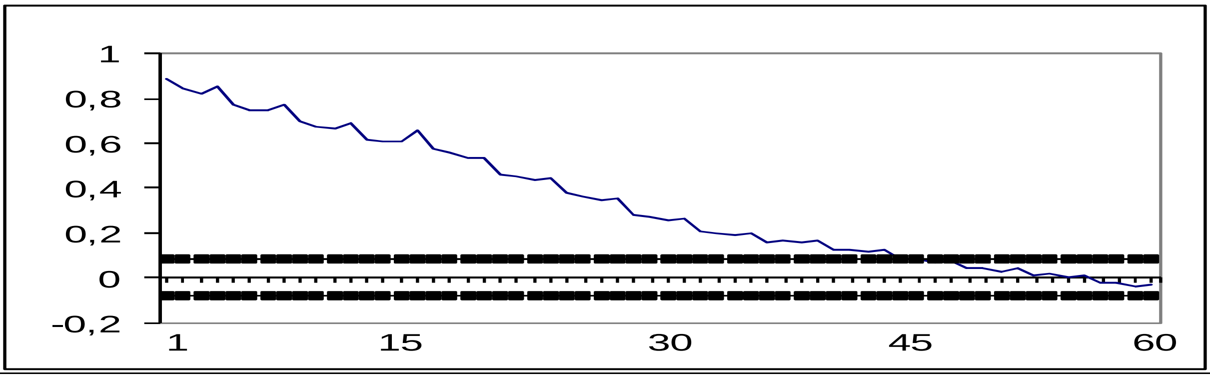
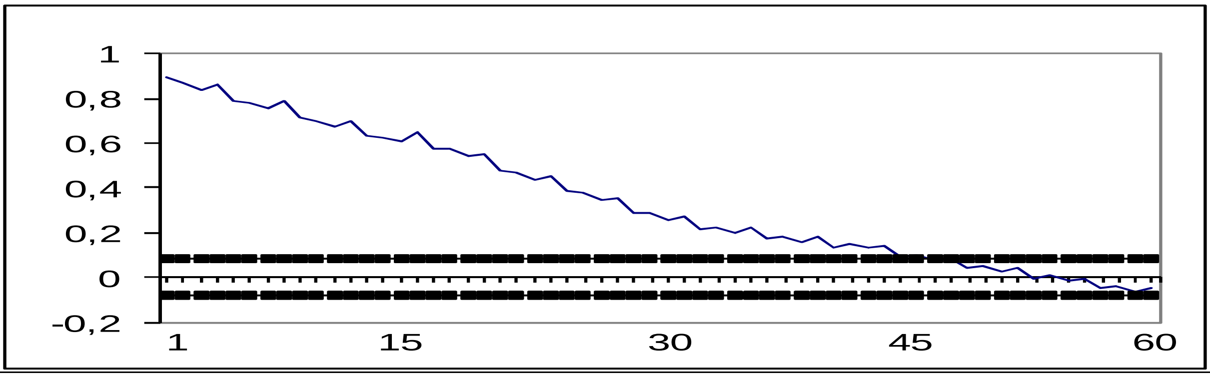


Figure 2: Correlograms of the time series

i) Total arrivals



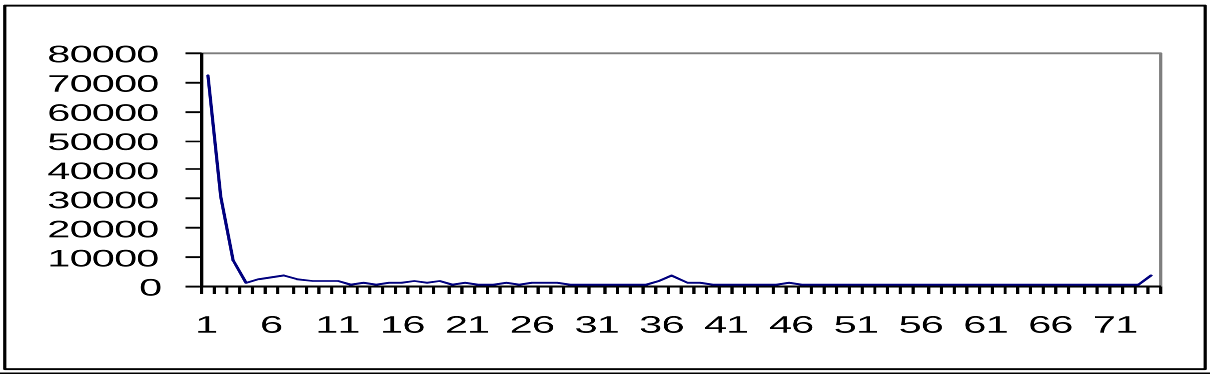
ii) Total departures



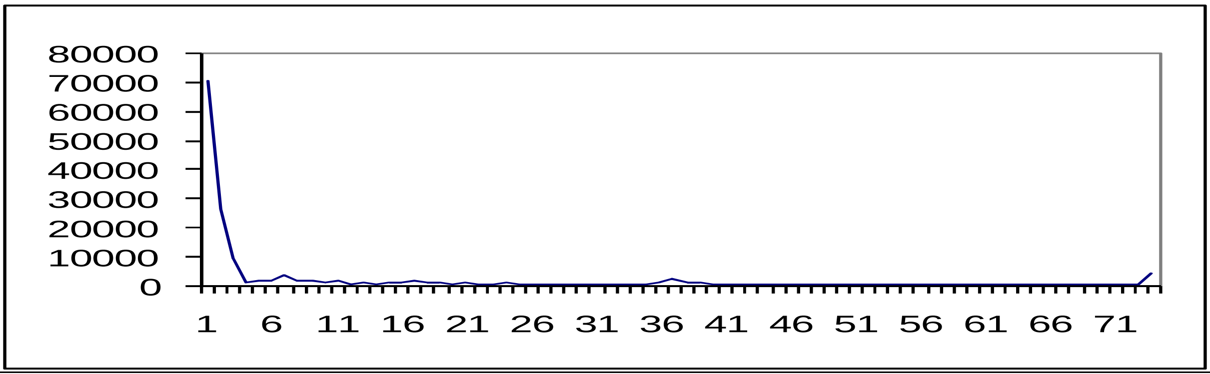
The thick lines in the correlograms represent the 95% confidence band for the null hypothesis of no autocorrelation.

Figure 3: Periodograms of the time series

i) Total arrivals



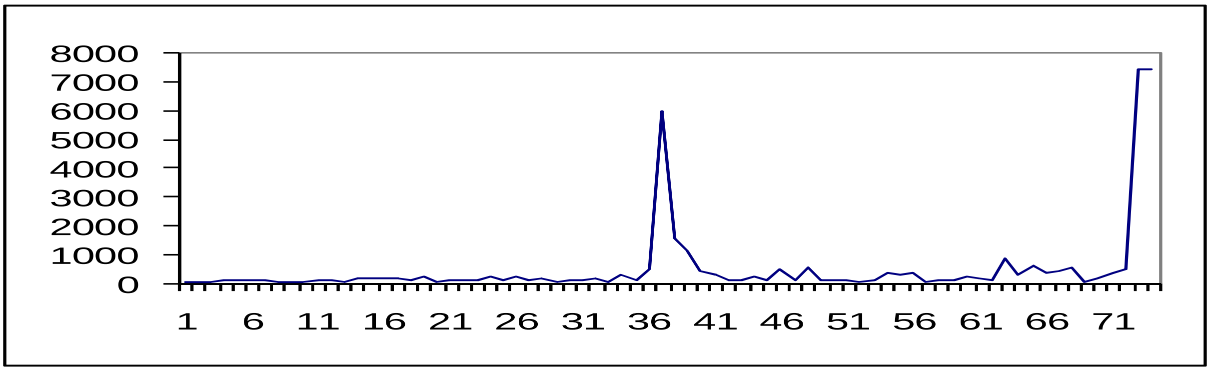
ii) Total departures



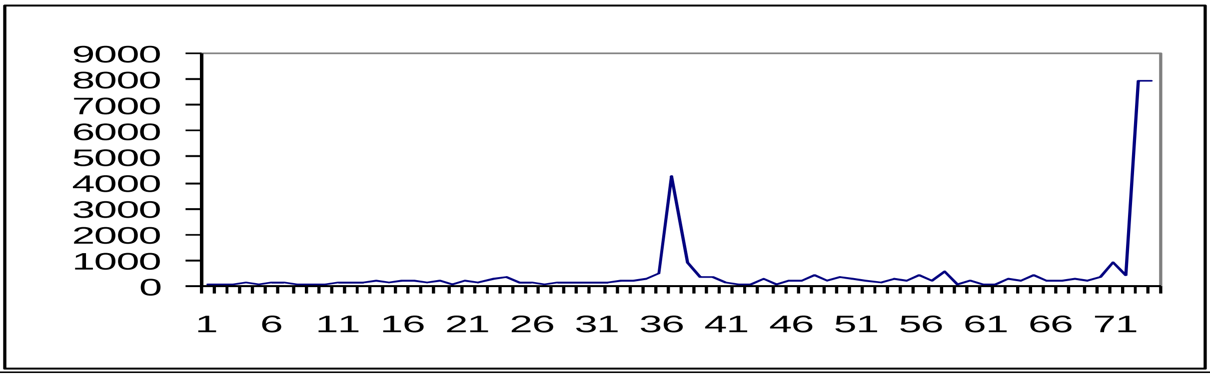
In the periodograms, the horizontal axis refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, $j = 1, \ldots, T/2$.

Figure 4: Periodograms of the first differenced time series

i) Total arrivals



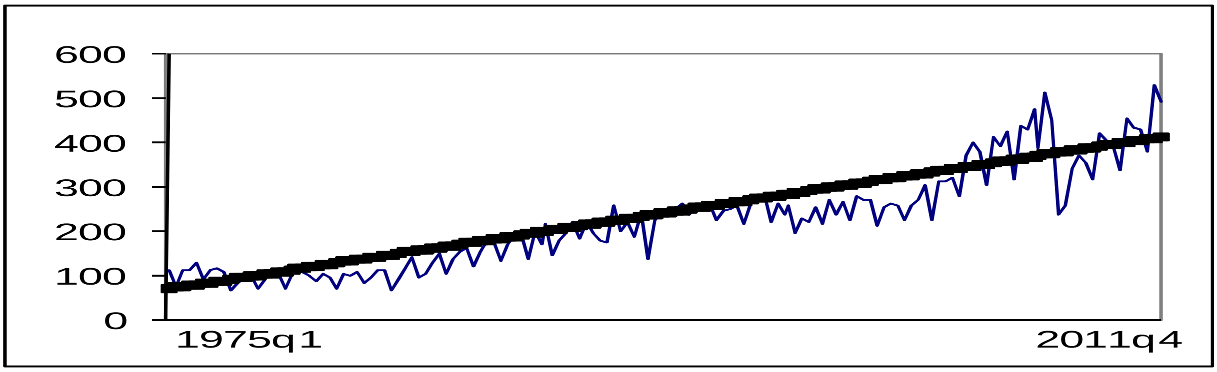
ii) Total departures



In the periodograms, the horizontal axis refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, $j = 1, \ldots, T/2$.

Figure 5: Original time series and deterministic trends

i) Total arrivals



ii) Total departures

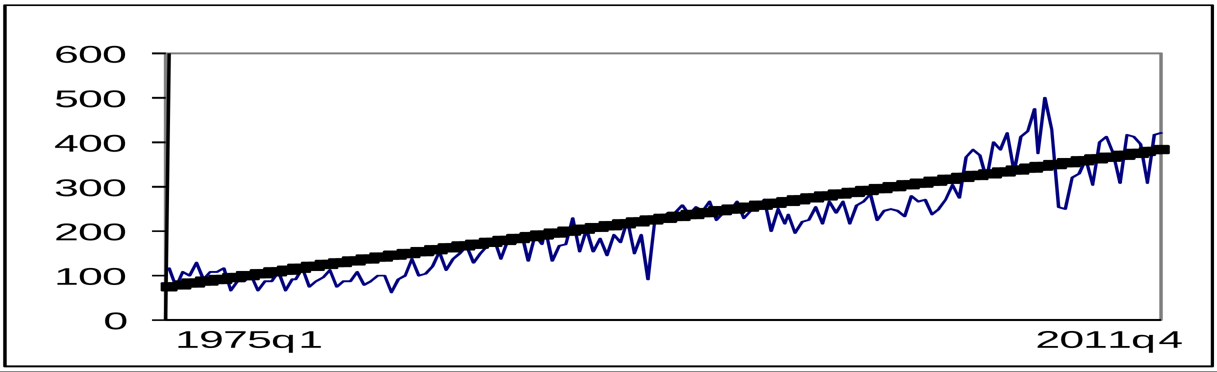
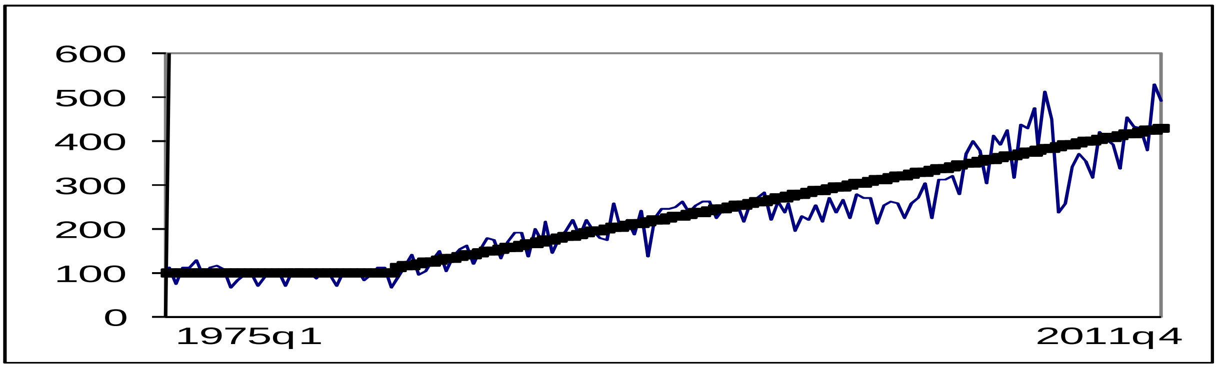


Figure 6: Original time series and segmented deterministic trends

i) Total arrivals



ii) Total departures

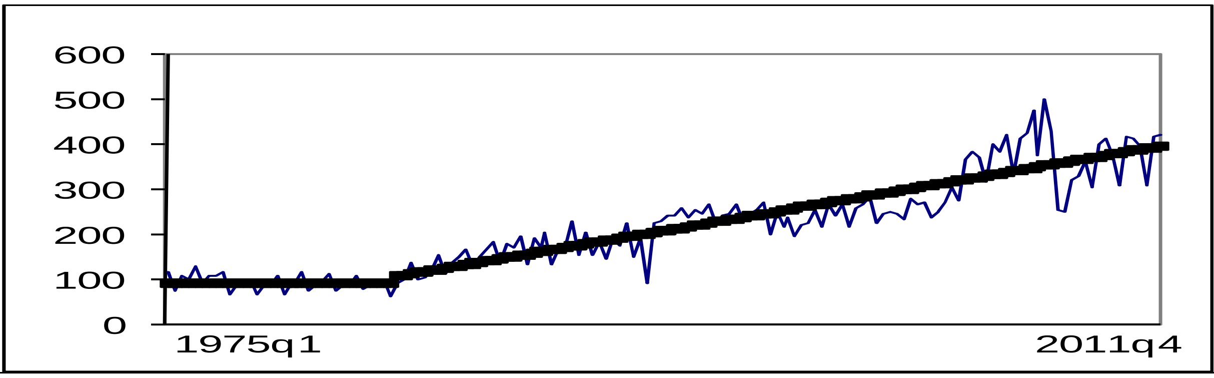


Table 1: Estimates of d and 95% confidence intervals

Series	No regressors	An intercept	A linear time trend
Arrivals	0.495 (0.391, 0.661)	0.525 (0.436, 0.652)	**0.424 (0.284, 0.613)**
Departures	0.506 (0.399, 0.701)	0.533 (0.448, 0.666)	**0.443 (0.299, 0.644)**

In bold, the significant cases according to the deterministic terms.

Table 2: Estimates of the parameters in the model given by the equations (6) – (8)

Series	d (95% conf. intv.)	β_0 (t-value)	β_0 (t-value)	Seasonal AR
Arrivals	0.424 (0.284, 0.613)	68.456 (2.870)	2.321 (7.881)	0.554
Departures	0.443 (0.299, 0.644)	70.933 (3.027)	2.101 (7.096)	0.481

Table 3: Estimated coefficients in the selected models with one structural break in the data

Series	Break date	First sub-sample coefficients				Second sub-sample coefficients			
		d	α_1	β_1	AR	d	α_2	β_2	AR
Arrivals	**1983q2**	**0.008** **(-0.316, 0.699)**	96.158 (36.817)	---	0.552	**0.382** **(0.213, 0.619)**	103.119 (4.899)	2.807 (8.714)	0.534
Departures	**1983q2**	**0.180** **(-0.124, 1.481)**	90.686 (25.286)	---	0.843	**0.402** **(0.237, 0.651)**	101.216 (4.663)	2.548 (7.547)	0.440