An analysis of seasonality in monthly per person tourist spending in Turkish inbound tourism from a market segmentation perspective

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Abstract

This study analyses seasonal variations in monthly per person tourist spending in Turkish inbound tourism from a market segmentation perspective. In this study a seasonal unit root test and recently developed decomposition techniques (TRAMO-SEATS, X-12-ARIMA) are used. It is found that there is a stochastic and strong seasonality in per person tourist spending data. The findings interestingly show that the seasonal pattern in per person tourist spending is considerably different from the seasonal pattern in tourist arrivals. The results have implications for decision-makers in tourism both at micro- and macro-levels in terms of effective resource allocation and market segmentation.

Keywords: Seasonality; Seasonal unit root test; Market segmentation; Turkish tourism

1. Introduction

Seasonality is one of the most salient and significant characteristics of tourism. A good understanding of seasonality in tourism is essential for the efficient operation of tourism facilities and infrastructure. Seasonality in tourism activity is not a particular characteristic of a single destination or country, as it is experienced in almost all countries and destinations in the world. Although seasonality in tourism has been examined in various studies, there is still need for further investigation of certain aspects of seasonality.

The concept of seasonality may be perceived to be familiar to many; however, there is no unique and precise definition of it. Seasonality may have different meanings attributed to it in different fields. As a general seasonality definition, Hylleberg (1992, p. 4) indicates that “seasonality is the systematic, although not necessarily regular, intra-year movement caused by changes in the weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by the agents of the economy. These decisions are influenced by the endowments, the expectations and the preferences of the agents, and the production techniques available in the economy”. In a tourism context, seasonality is usually described under two categories, namely natural and institutional (BarOn, 1975; Hartman, 1986). The natural type of seasonality is related to the regular and recurring temporal changes in natural phenomena at a particular destination, which are usually associated with climate, season of the year, precipitation, wind and daylight (Allcock, 1989; Butler, 1994). On the other hand, the institutional type of seasonality is the result of religious, cultural, ethnic, and social factors such as industrial holidays (Hinch & Hickey, 1997). The most important form of institutional type of seasonality is the school vacations in the summer. Butler (1994) states that there are three additional causes of seasonality which are social pressure or fashion (e.g. taking holidays at spas), sporting season (e.g. snow skiing), and inertia on the part of
holidaymakers, who continue to have holidays at a specific time of the year even though they are no longer restricted to this particular period.

Most of the literature describes seasonal variations in tourism activity that result in a number of negative effects on the destination and in the economy of that particular region or country (Edgell, 1990; Go, 1990; Jefferson & Lickorish, 1988; Laws, 1990; Lockwood & Guerrier, 1990; Poon, 1993; Speepenger, Houser, & Speepenger, 1990; Whelihan & Chon, 1991). McEnnif (1992) puts forward that tourism industry issues arising from seasonality are mainly concerned with the underutilization of capacity during the off-peak period. Because seasonality has significant implications for employment and capital investment, considerable efforts have been made by both the private and public sectors to reduce its negative influence in destination regions (Nadal, Font, & Rosello, 2004).

Although, in general, the main concern about seasonality focuses on the effective planning and use of resources during the off-peak period, the peak period which is taken as granted also needs particular attention, because the facilities during the peak period may become too crowded and this may cause difficulties in terms of maintaining service quality and satisfying tourists.

In exploring seasonality in a particular destination the figures of tourist numbers and total tourism receipts are used as seasonality indicators. The seasonal pattern in per capita tourist spending is generally overlooked. Both from the perspectives of individual firms and public policy making, substantial benefits may be obtained from understanding per person tourist spending and its seasonal variations. This would improve effective tourism policy development, planning and investment decision-making (Lim & McAleer, 2000, 2001) in terms of efficient resource allocation in production, marketing, investment, and financial planning (Krakover, 2000).

In Turkish inbound tourism a strong seasonality in tourist arrivals, hence in tourism receipts, is observed, as in many destinations. Large numbers of tourists visit Turkey for mainly sun and sea tourism during the warmer months of the year, which is identified as the peak period. In the remaining part of the year tourist numbers are sparse and hence the total tourism receipts in the off-peak period are relatively low compared with the peak period. However, there is a need to understand the off-peak period for better planning and effective resource allocation in tourism sector. One way of understanding the off-peak period better is to analyse the per person tourist spending both in the peak and off-peak period. For this reason this study concentrates on analysing seasonality in per person tourist spending.

In terms of its aim, this study can be considered as two-staged. First the seasonality aspect of per person tourist spending is empirically investigated using monthly time series data. Secondly, in the light of the seasonality findings, the inbound tourists can be segmented based on their level of expenditures. How seasonality can be related to segmenting tourist groups is analysed in the following section. Then, a brief account of the role of tourism industry in Turkey is presented in Section 3. In Section 4, seasonality in Turkish tourism industry is depicted, to be followed by description of the methodology used in the study in Section 5. The data and the findings of the research are presented and interpreted in Section 6, and Section 7 concludes.

2. Seasonality and segmentation in tourism

Developing and sustaining competitive advantage in competitive tourism markets largely depends upon understanding customers in terms of who buys what, when, why, where and how. Based on this understanding of customers, or potential customers, appropriate 4P strategies, namely, product, price, place and promotion, can be developed. In order to develop more appropriate marketing mix elements for potential customers with different needs, motives, attitudes, behaviours, age, income levels, spending patterns, life styles, etc., potential customers need to be put into separate sub-groups, called market segments. The “shotgun” approach rather than the “rifle” approach, i.e., targeting the whole market without segmenting it, usually ends up with wasted resources and unsatisfied customers.

In order to match the needs of distinct groups of tourists effectively, many studies have been carried out to explore and/or determine the particular characteristics of tourists in a specific segment, or the similarities possessed by the tourists in a specific segment (Chen, 2003; Hudson, 2000; Koc, 2002, 2004; Mok & Iverson, 2000; Nicholson & Pearce, 2000; Olsen, Warde, & Martens, 2000; Shoemaker, 1984, 1989 1994). In segmenting tourists, researchers have used prior (Hudson, 2000) and post hoc (May, Bastian, Taylor, & Whipple, 2001; Shoemaker, 1989) analyses.

In travel and tourism literature there have been a number of research studies over the years which used tourist expenditures as a segmentation variable. Earlier studies such as LaPage (1969), and Stynes and Mahoney (1980) did not prove to be useful as there were problems in terms of their ability to identify and distinguish different groups of customers depending on their level of expenditure. However, recent studies (Diaz-Perez, Bethencourt-Cejas, & Alvaro-Gonzalez, 2005; Legoherel, 1998; Spotts & Mahoney, 1991) have been able to discern heavy and light users. Spotts and Mahoney (1991), and Mok and Iverson (2000) claim that using tourist expenditures as a segmentation variable has superiority over using other variables. Mok and Iverson (2000), Spotts and Mahoney (1991), and Pizam and Reichel (1979) argue that expenditure-based segmentation satisfies all of the required characteristics of a segment put forward by Kotler (2003). These characteristics are measurability (the extent to which a market’s size and purchasing power in the segment can be measured), accessibility (the extent to which a market segment can be reached), substantiabililty (the extent to which a segment is large, i.e., substantial, and
profitable enough to deserve a different set of marketing mix), and actionability (the extent to which effective marketing mix decisions can be created and implemented).

This exploratory post hoc study aims at identifying the heavy and the light users segments in Turkish inbound tourism, by investigating the seasonal differences in per person tourist expenditures by using a seasonal unit root test and recently developed decomposition techniques. The study particularly focuses on the seasonality aspect of tourist expenditures per person by using monthly tourism data for the period of January 1992 and December 2004 with the aim identifying heavy and light users segments. Various researchers have put forward that heavy users of consumer products/services account for the large proportion of sales (Cook & Mindak, 1984; Kardes, 2002; Mok & Iverson, 2000; Rhim & Cooper, 2005; Solomon, Bamossy, & Askegaard, 2002) and they may need different sets of marketing mix strategies.

Although a phenomenal growth has been experienced over the past two decades, as will be explained in the following section, the review of tourism and hospitality literature shows that the issues on understanding tourists and segmenting the Turkish tourism market has been overlooked. Apart from one or two descriptive studies there has not been any research in terms of segmenting the Turkish market and analysing seasonal variations in per person tourist spending.

Moreover, a number of other reasons can be put forward to show the need for developing new segments in Turkish tourism market. For instance, Culligan (1992) proposed that the tourist's increasing desire for more novel, adventurous, and 'authentic' forms of tourism experience is a function of the decrease in utility associated with a decision to simply replicate previous experience. This means a move away from General Interest Tourism (GIT) towards Special Interest Tourism (SIT) (Brotherton & Himmetoglu 1997). Krippendorf (1987) argued that various changes occurring in the tourism market in general are in line with the developments of new modes of tourism consumption. He maintains that in the near future there will be a considerable decline in those tourists for whom hedonism is a principal travel motive, e.g. as in the case of sun and sea holidays, and for whom tourism is seen purely as a mechanism for recovery [rest] and liberation [escape from the ordinary]. Increasingly in tourism there is a move towards having holidays with more environmental and social content and the humanization of tourism activities (Krippendorf, 1987). In other words, there will be a move from GIT to SIT with decreasing utility in hedonistically motivated holidays. Zauhar (1994), Nadal et al. (2004) and Poon (1993) argue that future projections, with reference to tourism trends, indicate a tendency pattern of breaking free time into a series of blocks. This enables tourists to divide their holidays into several sub-periods, giving them the opportunity to take both summer and winter breaks, as they have more income at their disposal, thus permitting a variety of experiential stays within a single year.

3. Background

As the country’s second largest industry, tourism plays a crucial role in the economic development of Turkey. In addition to the phenomenal growth of tourist numbers and tourism revenues over the past two decades, the relative contribution of the tourism industry to Turkish economy has also shown a remarkable increase. The number of foreign tourists visiting Turkey grew from 2.1 million in 1984 to 17.5 million in 2004, and tourism revenues also increased from $840 million in 1984 to $12.1 billion in 2004. Additionally, the share of tourism revenues in the country’s gross national product (GNP) increased from 1.7 per cent to 5.3 per cent during the same period. The ratio of tourism revenues to total Turkish exports also increased from 11.8 per cent in 1984 to 25.2 per cent in 2004.

Tourism is an attractive industry for investment not only for developing countries such as Turkey, but also for developed countries due to the low capital requirement and the shortness of the realization period for investments (Williams & Shaw, 1992). Tourism makes a major contribution to the diversification of the economy and helps alleviate regional imbalances in developed countries. On the other hand, in developing countries tourism provides an export opportunity which is subject to relatively high growth rates and is less constrained (e.g. greater price flexibility and better employment opportunities) than the more traditional forms of export (Fletcher, 1995). Secondly, tourism is an important industry due to its multiplier effect it may have on the economy of the country. The multiplier refers to total addition to income resulting from initial expenditure within a sector and it measures the impact of extra expenditure introduced into an economy. Therefore, multiplier is concerned with the marginal rather than average changes.

The above explanations show how tourism can be a significant tool for economic development for many countries. As growth in tourism industry can affect growth in a variety of industries, in fact as many as 30, ranging from food, furniture, transportation, construction, to durable goods, a special attention needs to be paid to tourism industry by policy makers in Turkey. Obviously, the multiplier effect of tourism industry varies from country to country, and from region to region. Fletcher (1995) developed a tourism multiplier league estimated from input–output models for 30 countries, listing the multiplier effects of tourism in various countries, regions, cities, and tourist islands. In this multiplier league, Turkey’s multiplier value was found to be the highest (1.96) followed by the UK, the Republic of Ireland and Egypt, with values 1.73, 1.72 and 1.23, respectively. Thus, the high economic growth experienced recently in Turkey may be partially attributed to the remarkable growth in tourism activities in the country.

Another factor to show the importance of tourism industry for the economic development of Turkey is that the fact that tourism as a labour-intensive industry can create
significant amount of employment for Turkish economy, where the official figure of unemployment is 11 per cent (State Institute of Statistics, 2005), without taking substantial level of underemployment in the agricultural sector into account.

4. Seasonality in Turkish tourism

Seasonality in Turkish tourism is evident as can be seen from Fig. 1, which plots the monthly tourist arrivals and monthly total tourism receipts. When figures on tourist numbers visiting Turkey over the years are analysed it is seen that Turkey’s tourism activity is highly seasonal and sun and sea tourism plays a significant role in Turkish tourism. As can be seen from Fig. 2, the share of tourist arrivals between April and September (inclusive) constitute 68 per cent of total arrivals during the period of 1992–2004. These figures mean that Turkish tourism is highly vulnerable as to a large extent it is dependent on sun and sea tourism. By establishing the seasonal variations in per person tourist spending new market segments can be designed and the current vulnerability can be lessened.

It may be suggested that there will be a decline in the numbers of organized mass tourists who visit Turkey primarily for sun and sea holidays. This means that a proactive approach is required to develop and offer a variety of tourism products for the different segments of the tourism market. Otherwise, the growth rates in tourism activity in Turkey may not be sustainable.

Strong seasonality in the number of tourist arrivals and in the tourism revenues seems usual considering the type of tourism activity in Turkey. However, when per person tourist spending data, plotted in Fig. 3, are examined, it is seen surprisingly that a strong seasonality also exists in the per person tourist spending data which is the focus of this study. The methodology used in analysing the seasonality in this study is explained in the following section.

5. Decompositions for seasonal time series

Traditionally, statisticians and economists have dealt with the decomposition of time series usually into trend ($T$), seasonal ($S$), cyclical ($C$) and irregular ($I$) components, with the aim to detect the actual and historical condition of the business cycle, mainly by estimating and removing the seasonal component to obtain a plain picture of the state of the economy. However, the cyclical component is generally incorporated into the trend component. Hence, the three unobserved components can be either modelled as multiplicative

$$Y_t = T_t \times S_t \times I_t$$

or modelled as additive

$$Y_t = T_t + S_t + I_t.$$
constant over time, it is said that seasonality is deterministic; if seasonal pattern varies over years, then seasonality is viewed as stochastic. In fact, both of trend and seasonal components can be divided into two categories, deterministic and stochastic (Hylleberg & Mizon, 1989). A stochastic trend is known as a unit root process, similarly, a stochastic seasonal component is called seasonal unit root process.

There are several methods to estimate the unobserved components. A conventional approach is the use of regression analysis. In this case, a seasonal time series is regressed on a deterministic time trend and deterministic seasonal dummy variables, to obtain the estimates of the components. This method is appropriate only if a series contains deterministic components. Other methods use moving averages, filters, and ARIMA methodology to estimate the unobserved components. The most popular methods are the X-12-ARIMA and TRAMO/SEATS (Time Series Regression with ARIMA Noise, Missing Observations and Outliers/Signal Extraction in ARIMA Time Series) programs developed recently and used extensively especially by institutions such as the US Census Bureau, Eurostat, many central banks, etc. The basic seasonal adjustment procedure of X-12-ARIMA, which is an extension of X-11 method, decomposes a monthly or quarterly time series into a product or a sum of (estimates of) a trend component, a seasonal component, and a residual component, called the irregular component. The values for the estimated seasonal component are called seasonal factors. However, TRAMO/SEATS program decomposes series by additive method only.

The technical information about these two sophisticated programs, X-12-ARIMA and TRAMO/SEATS, can be found in Findley, Monsell, Bell, Otto, and Chen (1998) and in Gomez and Maravall (1996). In brief, both programs rely on the following scheme: RegARIMA and TRAMO are respectively pre-adjustment programs that remove some deterministic effects such as outliers and calendar effects, and identify and estimate linear stochastic models of the ARIMA-type for the remaining part of the series. It is that stochastic part which is then decomposed into seasonal, trend plus noise by X-12 and by SEATS. The program X-12 uses the forecasts made available by RegARIMA to extend the series before applying the adjustment filters and the trend filters. On the other hand, SEATS uses the model identified and estimated by TRAMO to derive the optimal filters for estimating the different components (Gomez & Maravall, 1996).

To determine whether a seasonal series contains stochastic trend and stochastic seasonals, Hylleberg, Engle, Granger, & Yoo (1990)—hereafter, HEGY—proposed a Dickey–Fuller-type seasonal unit root test for quarterly time series. The technical explanation of the HEGY test will not be given here considering the space limitation. If the test procedure is described in short, the test is based on an auxiliary regression which includes transformed variables, such that preserves the unit roots at the frequencies of interest and removes the other (seasonal or long run) unit roots at the other frequencies. The auxiliary regression can be augmented by the lagged values of the dependent variable, as is the case in the ADF test, and the seasonal dummies and trend can also be included, but these change the critical values. Beaulieu and Miron’s (1993) study extends the HEGY tests to monthly series, by the same manner. The test statistic is based on the following auxiliary regression:

\[ Y_{13t} = \text{constant} + \sum_{k=1}^{12} \pi_k Y_{k,t-1} + \text{trend} \\
+ \text{seasonal dummies} + \varepsilon_t, \]

where, \( Y_{13t} = (1 - L^{12})Y_t \), and \( Y_k \) are transformed variables of the time series under examination (\( X_t \)) for each corresponding frequency (see appendix). The null hypothesis of \( \pi_1 = 0 \), long term (at zero frequency) unit root, and of \( \pi_2 = 0 \) (at bi-annual frequency) is tested against the alternative hypothesis \( \pi_1 < 0 \) and \( \pi_2 < 0 \), respectively. For the seasonal unit roots at the other frequencies, one tests \( \pi_k = 0 \), where \( k \) is even, with two-sided test. Alternatively, one can test \( \pi_{k-1} = \pi_k = 0 \) with an \( F \)-statistic. To prove that no unit root exists at any seasonal frequency, \( \pi_k \) must be different from zero for \( k = 2 \) and for at least one member of each of the sets \{3,4\}, \{5,6\}, \{7,8\}, \{9,10\}, \{11,12\}.

6. Data and empirical results

The monthly tourist arrivals and tourism receipts (in million US dollars) data that cover the period from January 1992 to December 2004, are extracted from the Turkish Ministry of Culture and Tourism (2005) statistics released through the Internet. The beginning date is chosen on the grounds of availability of the monthly data. The calculation method of tourism receipts was changed by the Central Bank of Turkey in 2003. As a result, the spending of Turkish nationals who reside/work abroad while visiting Turkey has been counted as tourism receipts since January 2003. However, to maintain the continuity in the series, the additional changes since 2003 are not taken into account. Monthly per tourist spending series is generated by dividing the monthly total tourism receipts by the monthly total tourist arrivals.

To make an accurate inference about the seasonal movements in the per person tourist spending data, the time series properties of the data need to be determined. For this reason, first the Beaulieu and Miron version of the HEGY seasonal unit root test is applied to the monthly per person tourist spending series. The \( t \)-statistic results in Table 1 indicate that the null hypothesis of unit root is not rejected at 5 per cent level at zero frequency (long run), at bi-annual frequency, and at most of the other seasonal frequencies. The \( F \)-statistic results on the joint hypotheses reveal mixed results: the unit root hypothesis is rejected in four of frequencies, while the null hypothesis cannot be
rejected at $5\pi/6$ frequency. In conclusion, the test shows strong evidence for unit root at long run and at most of seasonal frequencies, indicating that the trend and seasonal components are better characterized as stochastic ones.

Having found that the trend component is stochastic and the seasonal pattern varies over time, a regression analysis using deterministic trend and deterministic seasonal dummies would yield spurious results. Therefore, X-12-ARIMA and TRAMO/SEATS methods to estimate the components are used. The software of these programs is distributed freely through the Internet by the US Census Bureau and by the Bank of Spain. These programs, in fact, have been developed to obtain seasonally adjusted series, however these programs have been used in this study to estimate the seasonal component (the seasonal factors). The multiplicative model in X-12-ARIMA has been used to obtain seasonal factors in percentages presented in Fig. 4.

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### Table 1

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>Test statistic</th>
<th>5% critical values $a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_1 = 0$</td>
<td>2.767</td>
<td>-3.28</td>
</tr>
<tr>
<td>$\pi_2 = 0$</td>
<td>-1.363</td>
<td>-2.75</td>
</tr>
<tr>
<td>$\pi_3 = 0$</td>
<td>-4.643*</td>
<td>-3.24</td>
</tr>
<tr>
<td>$\pi_4 = 0$</td>
<td>-0.104</td>
<td>-1.85</td>
</tr>
<tr>
<td>$\pi_5 = 0$</td>
<td>-3.161</td>
<td>-3.24</td>
</tr>
<tr>
<td>$\pi_6 = 0$</td>
<td>-2.127*</td>
<td>-1.85</td>
</tr>
<tr>
<td>$\pi_7 = 0$</td>
<td>-4.209*</td>
<td>-3.24</td>
</tr>
<tr>
<td>$\pi_8 = 0$</td>
<td>-2.467*</td>
<td>-1.85</td>
</tr>
<tr>
<td>$\pi_9 = 0$</td>
<td>-1.916</td>
<td>-3.24</td>
</tr>
<tr>
<td>$\pi_{10} = 0$</td>
<td>-0.676</td>
<td>-1.85</td>
</tr>
<tr>
<td>$\pi_{11} = 0$</td>
<td>-2.014</td>
<td>-3.24</td>
</tr>
<tr>
<td>$\pi_{12} = 0$</td>
<td>4.462</td>
<td>-1.85</td>
</tr>
<tr>
<td>$\pi_3 = \pi_4 = 0$</td>
<td>11.971*</td>
<td>6.23</td>
</tr>
<tr>
<td>$\pi_5 = \pi_6 = 0$</td>
<td>7.060*</td>
<td>6.23</td>
</tr>
<tr>
<td>$\pi_7 = \pi_8 = 0$</td>
<td>9.585*</td>
<td>6.23</td>
</tr>
<tr>
<td>$\pi_9 = \pi_{10} = 0$</td>
<td>2.326</td>
<td>6.23</td>
</tr>
<tr>
<td>$\pi_{11} = \pi_{12} = 0$</td>
<td>15.426*</td>
<td>6.23</td>
</tr>
</tbody>
</table>

Regression includes a constant, 11 seasonal dummies, and a time trend. $a$The critical values are taken from Beaulieu and Miron (1993). $b$Indicates rejection of the null hypothesis at 5 per cent level.

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Since TRAMO/SEATS has only additive model option, the logarithms of the series have been used to obtain seasonal factors in percentages. As can be seen from Fig. 4 the seasonal patterns estimated by two methods do not remain constant throughout the sample period. To take a closer look at the seasonal factors of the per person tourist spending, the seasonal factors for 2004 are given in Figs. 5 and 6, estimated by TRAMO/SEATS and X-12-ARIMA, respectively.

The seasonal factors estimated by the two methods have very similar monthly seasonal pattern. The increases and decreases in the average per person tourist spending in both figures are identical in the corresponding months, except the percentage points which are slightly different. In general, in January, August, September, October, and November tourists spend more than average, while from February to July (inclusive), and in December tourists spend less than average. August is the month that tourists spend highest on average, whereas in December per person tourist spending is the lowest, indicating visits of light users. Therefore, the findings of the study point out that by using seasonal factors, tourists visiting Turkey in August, September and October can de classified as the heavy users segment. On the other hand, tourists visiting Turkey in February, April, May and December can be classified as the light users segment.

Contrary to what may be expected, the seasonal pattern in per person tourist spending is considerably different from the seasonal pattern in tourist arrivals. As mentioned earlier, the peak period is taken for granted by many practitioners and researchers. They focus mainly on the off-peak period because of the negative impact of seasonality. However, this study finds that per person tourist spending in some of the months in the off-peak period, such as in October, November and January is higher than average, whereas it is lower than average in most of the months in the peak period, i.e., in April, May, June and July (see Fig. 5 and 6). Such information could be useful for tourism establishments in forming different target market segments based on different spending patterns in different months, and in designing their marketing mix strategies accordingly.
The reason for the highest level of per person tourist spending in August might be explained by the fact that tourists stay longer at the destination in August and hence spend relatively more money. In Turkey the average nights spent figure in August is 4.9 days compared with the annual average of 4.0 days. This is significantly higher than the average, and, to an extent, can explain the relatively higher level of per person tourist expenditure in August (see Figs. 5 and 6). Additionally, more tourists especially from neighbouring countries visit Turkey and stay longer in August. Nevertheless, using the average nights spent data for explaining differences in monthly expenditure levels for the rest of the months seems to be inadequate, as the correlation coefficient between monthly per tourist
spending and monthly average nights spent is found to be approximately 0.3, indicating a weak relationship. Furthermore, August is the busiest month of the year in Turkey in terms of yacht tourism, a type of tourism activity with significantly higher levels of per person tourist expenditure. About 30 per cent of yacht crews and 22 per cent of yacht passengers arrive in the month of August, during which yacht tours and yacht renting fees are significantly higher than the annual average for yacht businesses to skim excess demand. However, the effect of yacht tourism within total tourism revenues is not believed to be so significant.

Due to the lack of availability of monthly data regarding many aspects of tourism activity, i.e., monthly tourist data pertaining to the age groups, marital statuses, income levels, the types of transportation used, the types of accommodation used, the main reasons/motivations for tourists’ stays, etc., it is difficult to make deductions with a high level of certainty. However, the problem of the lack of availability of monthly data is not the problem encountered only in Turkey, as researchers such as Nadal et al. (2004) also refer to it in their research. Thus, it is recommended that future research in this field should concentrate on discovering other characteristics of tourists so that better profiles of segments are established. For instance, future research may concentrate on why average per person tourist expenditure figures are below average in June and July, while it is above average in January, as well as the differences in terms of the profiles of tourists visiting Turkey in these months.

The findings point out that the seasonality in per person tourist spending data appears to be stochastic rather than deterministic, i.e., the seasonal factors do not remain constant over the sample period. Hence, this finding may be associated with the findings of Poon (1993), Brotherton and Himmetoglu (1997), Krippendorf, (1987), Zauhar (1994) and Nadal et al. (2004) who suggested that there is a move away from traditional tourism activities in the particular period of a year.

The analysis of seasonality employed here also reveals the trend-cycle component estimated by the two methods. Fig. 7 presents the plot of trend-cycle movement of per person tourist spending in Turkey through the sample period. The effect of the factors such as economic, political, environmental, strategic, etc., can be attributed to the trend-cycle component. Both of the graphs in Fig. 7 indicate that per person tourist spending is the lowest in 1992, whereas it reaches its peak in 1998. Nevertheless, it seems to be rather stable since 1994, fluctuating around $600–$700. This result contradicts the prevailing belief commonly held in the industry that per tourist spending is declining, despite a steady rise in tourist arrivals.

7. Conclusions

This study has analysed seasonal variations in monthly per person tourist spending data in Turkish inbound tourism by using the seasonal unit root test and decomposition techniques.

The study indicates that the seasonal pattern does not remain constant throughout the sample period, i.e. the seasonal pattern is stochastic. The most important finding of the study is that the seasonal pattern found in per person tourist spending data is considerably different from the seasonal pattern of tourist arrivals and tourism receipts. Consequently, the estimated seasonal factors in per person tourist spending data can be employed in segmenting the tourist market as heavy and light users with respect to the monthly seasonal factors. Additionally, the findings of the research have implications particularly for customer analysis, competitor analysis, effective resource allocation and strategic marketing planning. Thus, the findings have relevance for both public and private sector practitioners and decision makers. Based on the expenditure levels of tourists found in this preliminary study, further research may be carried out to establish profiles or typologies of tourists visiting Turkey. This information would help decision makers segment the market and serve these segments better through developing appropriate marketing mix strategies.

Fig. 7. Estimates of trend-cycle components for per person tourist spending.
Appendix

The Beaulieu and Miron (1993) test is based on the following auxiliary regression:

\[ Y_{1t} = \sum_{k=1}^{12} \pi_k Y_{k,t-1} + \varepsilon_t. \]

The equation may include a constant, and deterministic components such as a time trend and seasonal dummy variables. The transformed variables \((Y_k)\) used in the regression are obtained from the following equations:

\[ Y_{1t} = (1 + L + L^2 + L^3 + \cdots + L^{11})X_t, \]
\[ Y_{2t} = -(1 - L - L^2 - L^3 + L^4 - L^5 + L^6 - L^7 + L^8 - L^9 + L^{10} - L^{11})X_t, \]
\[ Y_{3t} = -(L - L^3 + L^5 - L^7 + L^9 - L^{11})X_t, \]
\[ Y_{4t} = -(1 - L^2 + L^4 - L^6 + L^8 - L^{10})X_t, \]
\[ Y_{5t} = -\frac{1}{2}(1 + L - 2L^2 + L^3 + L^4 - 2L^5 + L^6 + L^7 - 2L^8 + L^9 + L^{10} - 2L^{11})X_t, \]
\[ Y_{6t} = \sqrt{\frac{3}{2}}(1 - L + L^3 - L^4 + L^6 - L^7 + L^9 - L^{10})X_t, \]
\[ Y_{7t} = \frac{1}{2}(1 - 2L^2 - L^3 + L^4 + 2L^5 + L^6 - L^7 - 2L^8 - L^9 + L^9 + 2L^{11})X_t, \]
\[ Y_{8t} = -\sqrt{\frac{3}{2}}(1 + L - L^3 - L^4 + L^6 + L^7 - L^9 - L^{10})X_t, \]
\[ Y_{9t} = \frac{1}{2}\left(\sqrt{\frac{3}{2}} - L + L^3 - \sqrt{\frac{3}{2}}L^4 + 2L^5 - \sqrt{\frac{3}{2}}L^6 + L^7 - L^9 + \sqrt{\frac{3}{2}}L^{10} - 2L^{11}\right)X_t, \]
\[ Y_{10t} = \frac{1}{2}\left(1 - \sqrt{\frac{3}{2}}L + 2L^2 - \sqrt{\frac{3}{2}}L^3 + L^4 - L^6 + \sqrt{\frac{3}{2}}L^7 - 2L^8 + \sqrt{\frac{3}{2}}L^9 - L^{10}\right)X_t, \]
\[ Y_{11t} = \frac{1}{2}\left(\sqrt{\frac{3}{2}} + L - L^3 - \sqrt{\frac{3}{2}}L^4 - 2L^5 - \sqrt{\frac{3}{2}}L^6 - L^7 + L^9 + \sqrt{\frac{3}{2}}L^{10} + 2L^{11}\right)X_t, \]
\[ Y_{12t} = -\frac{1}{2}\left(1 + \sqrt{\frac{3}{2}}L + 2L^2 + \sqrt{\frac{3}{2}}L^3 + L^4 - L^6 - \sqrt{\frac{3}{2}}L^7 - 2L^8 - \sqrt{\frac{3}{2}}L^9 - L^{10}\right)X_t, \]
\[ Y_{13t} = (1 - L^{12})X_t, \]

Where \(L\) is the lag operator, and \(X_t\) is the time series under examination. The meanings of the transformed variables are explained below. (Note that \(2\pi\) corresponds to a full cycle.)

\(Y_{1t}\) = Preserves the long-term (at zero frequency) unit root and removes the other seasonal unit roots at the other frequencies.

\(Y_{2t}\) = Preserves the unit root at (semi-annual) frequency (6/12) and removes the other (seasonal and long run) unit roots at the other frequencies.

\(Y_{3t}\) = Preserves the unit root at \(-\frac{\pi}{2}\) frequency (3/12) and removes the others.

\(Y_{4t}\) = Preserves the unit root at \(-\frac{\pi}{2}\) frequency (9/12) and removes the others.

\(Y_{5t}\) = Preserves the unit root at \(-\frac{\pi}{3}\) frequency (8/12) and removes the others.

\(Y_{6t}\) = Preserves the unit root at \(-\frac{\pi}{3}\) frequency (4/12) and removes the others.

\(Y_{7t}\) = Preserves the unit root at \(-\frac{\pi}{3}\) frequency (2/12) and removes the others.

\(Y_{8t}\) = Preserves the unit root at \(-\frac{\pi}{3}\) frequency (10/12) and removes the others.

\(Y_{9t}\) = Preserves the unit root at \(-\frac{5\pi}{6}\) frequency (7/12) and removes the others.

\(Y_{10t}\) = Preserves the unit root at \(-\frac{5\pi}{6}\) frequency (5/12) and removes the others.

\(Y_{11t}\) = Preserves the unit root at \(-\frac{\pi}{6}\) frequency (1/12) and removes the others.

\(Y_{12t}\) = Preserves the unit root at \(-\frac{\pi}{6}\) frequency (11/12) and removes the others.
