Seasonality in City Tourism: Concepts and Measurements

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Valeria Croce and Karl Wöber

4.1 Purpose and objective

This chapter intends to provide a conceptual basis to understand the forces shaping demand seasonal fluctuations. The most recent developments of research in this area are proposed as stimulus for discussion on the topic. It also offers an overview of the measurements most widely used to assess seasonality in tourism and proposes a methodology suitable to observe changes of seasonal patterns, illustrated with an empirical example on city tourism destinations.

4.2 Introduction

The analysis of seasonality patterns in urban tourism destinations is not a common practice. Cities are usually regarded to as year-round destinations, whose attractions, including museums, galleries and similar all-weather facilities, can attract visitors any time of the year. Their role as the "heart" of the social, political and economic life of a country makes them attractive to different types of tourists, such as business travelers and a variety of leisure segments, as well as package-tourists and independent travelers with special interests. Such dynamism and complexity makes the overall tourism demand for urban areas less dependent on climatic and seasonal factors.

As a matter of fact, urban areas are not immune to seasonal fluctuations of tourism demand. In Europe, the city tourism market presents a different degree of seasonality, whereby destinations with a single peak of demand compete against cities with a smooth, year-round distribution of visits. The motivation for variety in the pattern of monthly visits founds its roots in the complex system of factors underlying seasonal variations, which goes beyond the climatic seasons' rotation. Market mix characteristics, as well as marketing activities and product differentiation, also act in determining the attractiveness of a place in a specific time of the year (Butler and Mao, 1997; Baum and Hagen, 1999; Butler, 2001).

Seasonality has long been the object of tourism studies, but is still one of the most distinctive characteristics of the industry (Butler, 2001). Tackling seasonality is one of the common goals of strategy plans developed by tourism policy-makers and marketers (Baum and Hagen, 1999), mainly because of its impact on a destination's economic fabric, as well as on its socio-cultural and ecological environment. From a micro-economic perspective, the major problems are connected with the off-peak period, when the underutilization of inflexible facilities results in a loss of profits. This is especially true for the accommodation sector, where short-term responses to changes in the demand level are difficult to put into action. From a macroeconomic perspective, congestion of public places and infrastructure are the most frequent drawbacks (Koenig and Bischoff, 2005). A deep understanding of the causes underlying this phenomenon is required to correctly approach this problematic. At the same time, the availability of appropriate tools to assess seasonality and analyze the market is a desirable support to enhance the effectiveness of anti-seasonal strategies.

4.3 A conceptual framework of tourism seasonality

Seasonality is the regular, intra-year variation of visits to a destination, a concise definition, which entails the most distinctive features of this phenomenon. Seasonal variations occur every year and tend to manifest more or less in the same period and with the same magnitude (Bar-On, 1975). The characteristic of regularity discerns the seasonal component from accidental changes in the number of visits, due for example to sporadic events or non-recurrent conditions. The temporal frame of one year distinguishes the seasonal from the cyclic component – a phenomenon repeating regularly but over a longer period of time.

On a global level, seasonality is probably the most distinctive feature of the tourism industry (Butler, 2001). The seasonal nature of tourism derives from a few characteristics of the activity itself: holidaymaking requires a minimum amount of free time, which can typically be enjoyed at specific times of the year; holidays are by definition shorter than one year; holidaymakers predominantly practice outdoor activities, such as sightseeing, excursions and sunbathing, which they reasonably prefer to do under favorable weather conditions. Climate and natural conditions therefore play a determining role in understanding temporal variations of visits, though the spectrum of factors generating seasonality in tourism is in fact broader and more complex. Festivals, celebrations, destination marketing, local legislation and even habits produce effects on demand distribution over the twelve months. The comprehensive list of causes of seasonality is widely recognised (Butler and Mao, 1997; Baum and Hagen, 1999; Butler, 2001) and is illustrated in Table 1.

Natural factors refer to temporal variations of natural conditions, such as the temperature, sunlight, rainfall or snowfall. Among the natural factors, climatic aspects are stable and unchangeable conditions (Butler and Mao, 1997), although climatic changes will inevitably affect the shape of seasonality, as we know it today, in many of the world's regions (Smith, 1990), making them less certain and predictable. Predictable seasonal variations influence visitors' expectations about the destination climate prior to their visit when the decision about the holiday destination is made. Instead, weather changes during the day impact the *in situ* activities. On a global level, seasonal climatic differences are greater on higher latitudes than on the equator (Butler, 2000).

Institutional factors refer to human-made decisions affecting society and are enshrined in norms or legislation (Koenig and Bischoff, 2005). As far as tourism is concerned, the institutional factors that have an impact on travel have to be identified within those norms affecting the temporal pattern of work and leisure time, such as the legislation on industrial and school vacations or the calendar of public holidays. Calendar effects significantly have an impact on the seasonality of the series of tourism visits. Differences in the length of months,

Table 1 Factors generating seasonal patterns in tourism by type

Factors category	Category definition	Pull factors	Push factors
Natural	Temporal variations of natural conditions	Hours sunlight, snowfall, etc.	Temperature, rainfall, etc.
Institutional	Human-made decisions affecting the collectivity	Hotels opening season, sport season, etc.	School holidays, industrial holidays, etc.
Cultural/social	Human-made decisions affecting the individual	Cultural and religious celebrations, festivals, events, etc.	Fashion, tradition, inertia, etc.

leap years and moving holidays may produce a regular increase in the demand for a destination (Frechtling, 2007). These factors are predictable, but their occurrence may vary from year to year, such as moving holidays. The relevance of institutional factors may vary consistently across segments. Industrial and school holidays historically dominate the tourism industry and are still highly relevant for specific segments, such as families and industrial workers (Butler and Mao, 1997), but no longer significant for pensioners or DINKY (Double Income No Kids Yuppies). Growing trends such as the ageing population in western countries (the predominant tourists generating markets) and working time flexibility decrease the dependency of travel decisions on specific periods of the year, offering a fertile ground to concretely extend the main season(s). This is particularly true for urban areas – ideal destinations for a short break in addition to the main holidays. This habit became a successful product *per se* in Europe with noticeable results. Visitors' increased propensity to spread holidays in shorter and more frequent trips instead of consuming them in bulk can be easily exploited by urban areas to even out the distribution of visits.

Socio-cultural factors refer to human-made decisions concerning the individual and are therefore more closely connected with the travel motivation. Several forms of special interest tourism, such as cultural and religious tourism, are subject to the factors in this category. Pilgrims travelling to attend a religious celebration or football fans' trips to matches during the season are two examples of seasonal visits connected to special interests. Fashion and industry trends also have an impact on the association of a destination with a specific time of the year since the origins of tourism. It is renowned that the habit of spending winter holidays in mountain destinations started at the beginning of the last century when the practice of snow sports became a recreational activity.

Since the activity of tourism interests at least two locations, the origin and the destination, factors can alternatively act as an attractive (pull) or repulsive (push) force (Lundtorp, Rassing et al., 1999). This aspect is known as the spatial component of seasonality. For each specific origin-destination pair, the final pattern of visits results from the specific, concurrent manifestation of influencing factors at the two locations. The presence of each factor, as well as its strength and the type of impact, may consistently vary for each combination of origin-destination. The mismatch of climate conditions between the origin and the destination, for instance, opens up to opportunities for season extensions. As a typical example for European destinations, the difference of climate conditions makes Mediterranean regions more attractive to Northern Europe markets in the spring and autumn when the climate is mild and not too hot.

Questions

Several factors may produce seasonal variations of demand. Which are the main factors causing seasonality in tourism? Which are the three main forms of seasonality affecting city tourism destinations?

The forces shaping the flow of visits do not act in isolation, and the external environment also influences their impact. Firstly, all of the factors may be constrained by supply-side conditions (for instance, hotels' closing period), which alter the availability of services at the destination or the availability of labour force. In some urban areas, whole industrial sectors close for a one- or two-week period with consequent desertification of the area. For these cities, the effect of holidays in their source markets would be nullified by the lack of services. Secondly, demand patterns are shaped by the action of these demand- and supply-related factors both directly and through the mediation of modifying factors, reflecting the conditions of the competitive framework, such as relative prices or market diversification (Butler and Mao, 1997; Butler, 2001). These factors modify the seasonal patterns of demand *mutatis mutandis* the conditions in the origin and in the destination mentioned above.

Patterns of destination demand are shaped by the system of causes described above and typically assume one of the following three forms:

1. No peak destinations, which are characterised by a smooth distribution of international arrivals at the destination with no significant difference between peak and non-peak periods, such as for the city of Brussels;
2. One peak destinations present a concentration of arrivals in one specific period of the year; the peak may take the shape of a pyramid with a steep rise and decline in visits, as in the case of Nice, or be accompanied by shoulder seasons, such as the city of Copenhagen; a shoulder season may be present before and (or) after the peak;
3. Two peaks destinations present a bimodal distribution of visits, which are concentrated in two distinguished periods of the year. The magnitude of the peaks may be equal (as for Milan) or different. In this case seasons can be defined as 'major' and 'minor'.

The no peak distribution is the shape generally attributed to cities (Hall and Page, 2003), though it is evident from Figure 1 that urban destinations cover different degrees of seasonality. For Brussels seasonal variations are indeed negligible, while for destinations like

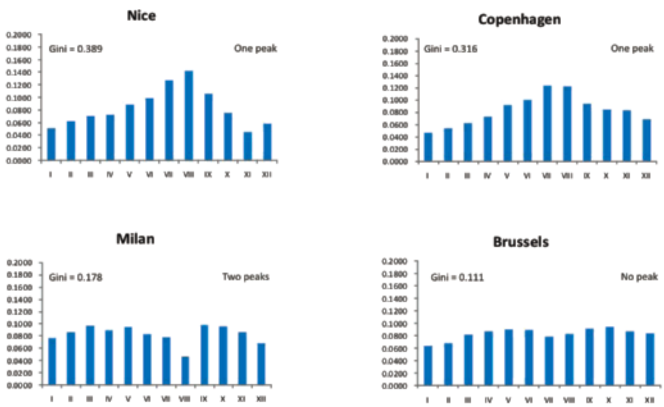

Fig. 1 Seasonal patterns of European cities

Nice and Copenhagen seasonal extension is a goal. Destinations with an unusual pattern like Milan, with a trough in August, benchmarking the distribution of visits against competitors may be helpful to support the development of appropriate marketing strategies. To enhance the efficiency of anti-seasonality strategies, the impacts and the possibilities of a season extension need to be accurately evaluated (Lundtorp, 2001). The measurement of the phenomenon and of its central characteristics is a valid support to provide a first understanding of seasonality intensity, but more sophisticated tools are also applicable to efficiently tackle the problem, as illustrated in the next chapters.

Discussion Point

The determinants of seasonal patterns

Most of the studies in tourism seasonality focus on longitudinal studies involving time series decompositions with the aim of modelling demand with or without the seasonal component. Relatively few authors have examined methods to quantify and compare the degree of seasonality or to assess the importance of factors generating seasonal patterns (Koenig and Bischoff, 2005). Recent research in tourism seasonality focuses on identifying the factors determinant in shaping seasonal demand patterns. Jeffrey and Barden (2001), for example, performed a Principal Component Analysis (PCA) relating the characteristics (location, service quality, management and market aspects) of a sample of hotels in England to their monthly occupancy rates, and found that hotel occupancy performance mainly depends on the type of market served (Jeffrey and Barden, 2001). Rosselló et al. (2004) performed a regression analysis in a study investigating the relationship between a set of economic indicators (per capita Gross Domestics Product, relative prices, exchange rates and consumer price index) and the development of seasonality, finding that when a fall in relative prices occur, seasonality tends to be less acute, while an exchange rate benefiting the tourists results in an increase of demand in the peak season (Rosselló, Riera et al., 2004). Similarly, Capó et al. (2006) used regression analyses to identify which accommodation-related factors determine fluctuations in hotels' opening period for the Balearic Islands. Their findings suggest that the higher the quality category of the hotel, the longer the opening period will be (Capó, Riera, et al., 2006).

4.4 Measuring and analysing seasonality

Depending on the aim of the analysis, a range of different units can be used to analyze the seasonal pattern of a destination. Reflecting the effective data availability, most of the studies on seasonality analyze tourism demand patterns using statistics on the arrivals or overnights of visitors, the former expressing tourists' demand for a location and the latter the load of tourists staying at the destination. Visits can be measured as flow (visitors per time unit) or stock (visitors at a certain point in time). Flows are generally preferred both for statistical and practical reasons, the most straightforward being that stocks can be derived from flows through aggregation (Lundtorp, 2001).

In statistics, seasonality refers to the series component characterizing a distribution (V_t) with movements recurring similarly during a particular time of the year (Frechtling, 2007). In a classical decomposition approach, the seasonal component (S_t) can be isolated from the others, namely the trend (T_t), the cycle (C_t), together with the error term (e_t) (as in 1). The trend-cycle component is generally estimated by the means of smoothing techniques, such as the moving average (Balladori, 1994).

(1) $V_t = T_t \times C_t \times S_t \times e_t$ where $t = 1, 2, ..., 12$

If the time series model is an additive, the seasonal component for a time period is simply calculated as the difference between the actual value of visits (V_t) and the non-seasonal value (T_t+ C_t) for each month *t*. If the model best fitting the data series is multiplicative, a widely used method to extrapolate the seasonal component is the ratio-to-moving-averages decomposition method, whereby the seasonal ratios are computed dividing the actual observations by the corresponding moving average values (2): a value of the ratio greater (lower) than one suggests the presence of a seasonal component.

(2) $S_t \times e_t = \frac{V_t}{T_t \times C_t}$ where $t = 1, 2, ..., 12$

In a Box-Jenkins approach, seasonality should be identified examining the autocorrelation coefficients, whereby a high correlation indicates seasonality for the corresponding period (for a more detailed description see Frechtling, 2007).

Yacoumis (1980) suggests the use of the peak-to-average ratio (*R*), which is obtained by dividing the highest peak of the distribution of visits (Max V_t) by the average value (3), as synthetic measure for the amplitude of the seasonal component within the year. The seasonality ratio range is restricted to one and 12: the lower the value, the more equal the distribution of visits.

(3) $R = \frac{MAX\ V_t}{\overline{V}}$ where $t = 1, 2, ..., 12$

Lundtorp (2001) instead suggests the calculation of an index of homophily (4), obtained by inverting the terms of formula (3) to emphasise the similarity between observations. Taking MAX V_t as an indicator of a destination's total capacity, it renders a measurement of the average occupancy rate for a specific year.

(4) $\omega = \frac{\overline{V}}{MAX\ V_t}$ where $t = 1, 2, ..., 12$

Measures of dispersions can also be used to describe central characteristics of a seasonal distribution. Yacoumis (1980) also suggests the use of a coefficient of seasonal variation, which synthesises the dispersion of monthly visits around a non-seasonal value. The coefficient is calculated as the standard deviation of seasonal indices. For each period, for instance a year, seasonal indices are expressed as the ratio between the monthly value and the annual average. The lower the standard deviation, the less seasonal the distribution is.

As a common feature, these indicators assess the amplitude of seasonality based on the central moments of the distribution, but do not provide any information concerning changes in the distribution. Changes in the seasonal pattern have a two-fold nature: they may consist of a 'pure change' when an increase in the visits amplifies the existing seasonal pattern, or a 'pattern change' when visits shift from one month to another (Sutcliffe and Sinclaire, 1980). The analysis of pattern changes is of particular relevance in tourism, since they can be directly the target of specific policies as well as the indirect effect of a strategy aimed to changes in the product or guests mix. The next paragraphs present two methodologies suitable to observe changes of demand's seasonal patterns, illustrated with an analysis of the monthly demand for 20 major cities in Europe.

4.5
Assessing seasonality in city tourism demand

The 20 destinations selected for the analysis account altogether for approximately 180 million[1] bed-nights a year, and represent the most relevant tourism destinations in the European city break market (see Table 2). The focus of the analyses describe later in this paragraph is to observe and compare the typical seasonality of these cities. A 'typical' year is rather difficult to identify, since most of the destinations in exam hosted non-recurrent events in the reference period, which biased the distribution of visits. Vienna and Amsterdam, for instance, celebrated the Mozart and the Rembrandt year in 2006, respectively. Though such celebrations consist in a calendar of themed activities throughout the whole year, the events in the calendar are not all of equal importance and impact. Thematic years therefore produce the same effects as one-time events like the FIFA World Championship, hosted by German cities in July 2005. To smooth the impact of non recurrent events, the series of monthly bed-nights have been averaged over the period 2003–2007[2]. The averaged series of monthly bed-nights have been used as basis for the analyses described in what follows. The data series have been retrieved from TourMIS, the online information system for tourism statistics[3].

1 Average value for the period from 2003 to 2007.
2 The averaged monthly series of bednights have therefore been calculated on a different number of observations, according to data availability in TourMIS. For the majority of the cities, average values result from five (56%) or four (18%) observations. The remaining quota (26%) is equally shared within cities for which the average is calculated on a three- or two-year basis.
3 The data for the city of Madrid have been retrieved from the database of the Spanish national statistics office (www.ine.es). For the other cities, the data have been retrieved from TourMIS (www.tourmis.info).

Software

TourMIS is a Marketing-Information-System for tourism managers whose major aim is to provide information and decision support for tourism managers and scholars. TourMIS not only provides on-line tourism survey data, but also various tools to transform data into precious management information. In its aim of supporting the decision-making and planning process of tourism managers (see www.tourmis.info).

4.5.1
Measuring and benchmarking the amplitude of seasonality

For its sensitivity to distribution skewness, the Gini coefficient is sensitive to both pure and pattern changes and can correctly classify different seasonal patterns (Tsitouras, 2004). Named after the Italian statistician Corrado Gini who first developed the formula in 1912, the coefficient was first used to measure the degree of income inequality across countries and later adopted by a wide range of study areas, among which tourism (Sutcliffe and Sinclair, 1980; Yacoumis, 1980; Wöber, 1997; Lee and Kang, 1998; Rosselló, Riera et al., 2004). The coefficient renders a measurement of the area lying between a uniform distribution and the Lorentz curve, which is the curve connecting the cumulative percentage of the individual monthly shares ranked ascendant according to their size. To analyze the seasonality in visits to a destination, the coefficient can be formally expressed as:

$$(5)\ G = 1 - \frac{2}{n}\left[\sum_i X_i - \sum_i Y_i\right] \text{ where } i = 1, 2, \ldots, n$$

where X_i is the cumulative relative frequency of monthly visits ranked ascendant, Y_i is the rank

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Table 2 Average bednights and values of the Gini coefficient in 20 European cities and the country where they are located

(a) City	(b) Average bednights (***)	(c) Gini (city)	(d) Country	(e) Gini (country)	(f) Difference (c – e)
Amsterdam	8,233,380	0.157	The Netherlands (*)	0.220	–0.063
Barcelona	11,361,518	0.151	Spain (**)	0.698	–0.547
Berlin	15,421,408	0.217	Germany	0.182	0.035
Brussels	4,967,870	0.111	Belgium	0.225	–0.114
Budapest	5,979,762	0.308	Hungary	0.274	0.035
Copenhagen	4,183,104	0.316	Denmark	0.430	–0.113
Florence	5,665,838	0.224	Italy	0.304	–0.080
Hamburg	6,719,143	0.174	Germany	0.182	–0.008
Lisbon	5,292,236	0.232	Portugal	0.211	0.021
Madrid	12,276,088	0.114	Spain (**)	0.698	–0.584
Milan	6,866,792	0.178	Italy	0.304	–0.126
Munich	8,294,250	0.187	Germany	0.182	0.005
Nice	6,923,115	0.389	France	0.145	0.243
Paris	33,145,429	0.118	France	0.145	–0.027
Rome	16,120,370	0.214	Italy	0.304	–0.090
Stockholm	4,992,124	0.247	Sweden	0.137	0.109
Valencia	3,048,269	0.158	Spain (**)	0.698	–0.540
Venice	5,627,561	0.245	Italy	0.304	–0.059
Vienna	9,391,701	0.244	Austria	0.255	–0.012
Zurich	3,046,190	0.155	Switzerland	0.152	0.003
Average		0.207		0.303	
St. Dev		0.072		0.185	

(*) source: CBS
(**) source: EUROSTAT
(***) average calculated on the monthly bednight series 2003–2007

of fractals and n is the number of fractals. The Gini coefficient is terminated in the range from 0 to 1, whereby the lower the value, the more equal is the distribution. One property of the coefficient is indeed to return a value of zero in presence of a uniform distribution, regardless of the number of observations. This can lead to misinterpretation when using the coefficient for benchmarking purposes, since the Gini would return the same value for destinations having an equal distribution of the visits over the whole year or just a short season. Given that tourism series are typically observed at monthly frequencies, this shortcoming can be removed adopting the twelve-month rectangular distribution as fix reference (Tsitouras, 2004).

Each destination is then benchmarked against the ideal uniform distribution over the twelve months. Another desirable property of the Gini coefficient is that it takes into account all the points of a distribution, and is therefore sensitive to changes in its skewness both in case of additional demand and share transfers. If the share of visits increases in the lower-ranked shares (the off-peak months) both because of a 'pure change' (additional demand) or of a 'pattern change' (visits swap from the higher to the lower season, for instance because of an event), the value of the Gini coefficient decreases. Thirdly, a coefficient calculated on shares is less influenced by extreme values, and to be preferred to indicators based on measurements of the standard deviation (Lundtorp, 2001).

The values of the coefficient for each city and the average value for the whole group of destinations are listed in column *c* of Table 2. The values of the coefficient can be used to assess the relative amplitude of seasonality for one destination against its main competitors and the market (in this exercise the group of city). The values of the Gini range from a maximum 0.389 to a minimum of 0.111 (standard deviation = 0.072), denoting overall a low concentration of visits at specific periods of the year. A few important exceptions can be discussed. Figure 2 shows the differences calculated between each city's value and the group average (Gini = 0.207), and with the Gini coefficient of the country where the city is located (calculated on average monthly shares for 2003–2007). In both series, the city is the main object of comparison, therefore a positive (negative) value means that the value of the Gini for the city is higher (lower) than that of its term of comparison. For most cities, the difference lies between ±0.05 points. For the outliners, namely Nice (+0.182), Copenhagen (+0.109) and Budapest (+0.101), seasonality can be seen as an issue to tackle, since the distribution of the visits is rather concentrated. In Brussels (–0.096), Madrid (–0.093) and Paris (–0.089) tourism authorities may prioritise other issues, since the demand for these destinations is almost independent from specific times of the year.

Questions

Which are the main properties of the Gini coefficient which make it a suitable measure of the amplitude of seasonality? Why is it important to use a fix reference when applying the Gini coefficient for measuring tourism demand seasonality?

Different regional levels may be affected by different degrees of seasonality (Yacoumis, 1980). The Gini can also be used to compare the degree of seasonality within the 20 cities and the country where they are located. In four

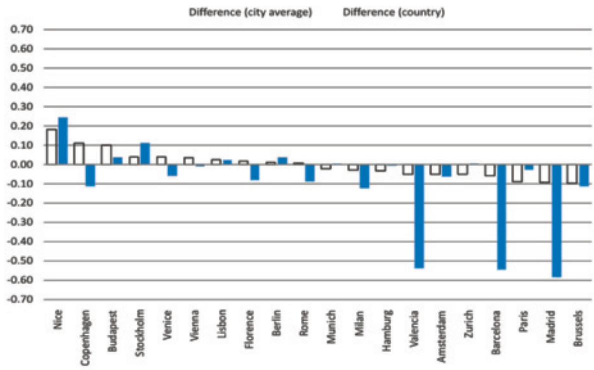

Fig. 2 Differences based on the Gini coefficient values (cities and countries)

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cases (Hamburg, Munich, Vienna and Zurich) the amplitude of seasonality in the urban center matches that of the whole country. For most of the remaining cities the monthly series of bed-nights are more evenly distributed than that of the respective countries. The picture provided by this group of cities reinforces the idea that tourism in urban areas is less seasonal than visits directed towards peripheral areas.

For some destinations, the analysis of seasonality in relative terms provides a more realistic understanding of the phenomenon. Copenhagen for instance scores as the second most seasonal destination among this group. Within the national context, the series of bed-nights in the capital city is much less seasonal than that of the whole country, as the coefficient value for Copenhagen is approximately one point lower than value for Denmark. Similarly, the Spanish cities' performances, which are rather good in comparison to the group of cities, are outstanding if compared with the highly seasonal national context. These results suggest that in a national context the problem of seasonality should be approached with appropriate measures at each level.

Analyzing city tourism seasonality with TourMIS

The analysis of destination's seasonality has also been implemented in TourMIS (www.tourmis.info). The function can be found in the 'City tourism in Europe' menu. The link 'monthly data' on the top of the page has to be selected to access the section concerning the monthly series of arrivals and bed-nights. A click on the 'Assessing seasonality' link gives access to a drop down menu where selecting the destination for which the analysis has to be performed. The type of time series (arrivals or overnights), the source market and the year of reference can also be specified at this stage. This last step is particularly important to obtain target-oriented results. In fact, investigating the aggregate flow of visitors to a destination over one year is more appropriated to make a resolution about the allocation of an event in the calendar, while the analysis of the overnights distribution for a specific market is more meaningful if a decision about a marketing campaign must be made. The outcome of the query is presented in a tabular form (see below) where the absolute and relative value of the variable selected and the Gini coefficient are displayed. The value of the Gini coefficient for all the destinations in the system is displayed in the table at the bottom of the page to facilitate the benchmarking of the amplitude of seasonality among competitors in the city tourism market.

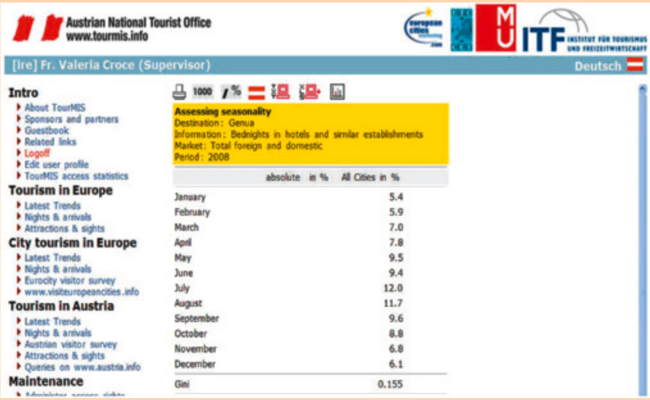


Fig. 3 Assessing seasonality in TourMIS (www.tourmis.info)

4.5.2 Benchmarking seasonal demand patterns

At the operational level, the analysis of seasonality should also provide insight about the temporal ordering of the bed-nights distribution which effectively enables decision-makers to design appropriate anti-seasonal policies. The next analysis is intended to compare the demand for the same 20 European cities, and assess how similar their seasonal patterns are. The aim here is to capture the dynamics of demand concentration over time, to identify groups of cities competing for the same markets, in the same periods. The similarity structure has been investigating using multi-dimensional scaling (MDS), a method widely used in marketing studies.

MDS analyses are based on proximity measures which are used as input for the algorithm. In this study, Pearson's bi-variate correlation coefficients have been used to assess the similarity between each pair of destinations. The coefficients render a measurement of the degree of association between two distributions, whereby a value of 1 means a strong correlation (-1 stands for a strong negative correlation) and 0 means no correlation at all. The output is a square, symmetric table (see Table 3), where the cities are both the object of the analysis (row) and the element of comparison (column). The result is an appropriate measure of the similarity of series' monthly behavior for each pair of destinations.

To investigate similarities in a systematic way, the Alternative Least Square Scaling (ALSCAL) algorithm (Takane, Young et al., 1977) has been performed on Euclidean distances derived from the correlation coefficients matrix. In general, multi-dimensional scaling algorithms serve to configure a set of objects, each defined in terms of *n* attributes, as a point in a space with lower dimensions. Iterations of the algorithm minimise the differences so that the distances between points in the space have the strongest possible relation to the observed proximities. Using correlation coefficients as input, two close points on the multidimensional map represent two objects with a similar demand pattern, and *vice versa*. The adequate number of dimensions for the perceptual map depends on the Stress, a measure assessing the goodness of fit, whereby the lower the value of the Stress, the better the fit is (Backhaus 2000). The orientation of the axis is instead arbitrary and should provide the best visual support to the interpretation of the configuration. The identification of the "meaning" of objects' positioning can be supported by external information, such as additional objects' properties, or using the inputs as stimuli for interpretation. Hints on the interpretation of the maps were derived from the same input data.

The first analysis is based on the average series of bed-nights for the domestic and international demand. The scaling process was performed with a highly satisfactory fit[4]. The outcome is visualized in Figure 4. The configuration shows a concentration of cities in the center left area of the diagram and a few points spread around the figure. The cities in the main group (Zurich, Amsterdam, Vienna, Budapest, Lisbon, Valencia, Hamburg, Berlin, Barcelona, Venice, Paris and Florence) are typified by a bi-modal distribution of bed-nights, where the importance of the two peaks tends to be remarkably different for the destinations positioned higher on the vertical axis. Within this group, the demand pattern of Zurich, Amsterdam, Vienna, Budapest, Lisbon, Valencia and Hamburg presents a major season (typically around August) and a minor season (around April), while in the remaining cities (Berlin, Barcelona, Venice, Paris and Florence), the two seasons are of equal magnitude and tend to merge into one extended season (from spring to autumn).

4 For the 2-dimensions plot the S-Stress = 0.07 and the Stress = 0.03. For the 3-dimensions model the values were respectively 0.04 and 0.02.

Table 3 Similarity of the distribution for 20 European cities (Pearson's bi-variate correlation coefficients)

Correlations										
City	Paris	Rome	Berlin	Madrid	Barcelona	Vienna	Munich	Amsterdam	Nice	Milan
Paris	1	.800**	.930**	.636*	.858**	.908**	.903**	.791**	.618*	.095
Rome	.800**	1	.844**	.848**	.844**	.653*	.712**	.675*	.392	.55
Berlin	.930**	.844**	1	.563	.947**	.940**	.941**	.910**	.740**	.042
Madrid	.636*	.848**	.563	1	.561	.371	.462	.327	–.063	.720**
Barcelona	.858**	.844**	.947**	.561	1	.825**	.901**	.919**	.750**	.133
Vienna	.908**	.653*	.940**	.371	.825**	1	.917**	.868**	.782**	–.223
Munich	.903**	.712**	.941**	.462	.901**	.917**	1	.828**	.781**	–.046
Amsterdam	.791**	.675*	.910**	.327	.919**	.868**	.828**	1	.798**	–.179
Nice	.618*	.392	.740**	–.063	.750**	.782**	.781**	.798**	1	–.397
Milan	.095	.55	.042	.720**	.133	–.223	–.046	–.179	–.397	1
Hamburg	.889**	.800**	.981**	.522	.963**	.923**	.922**	.955**	.749**	–.022
Budapest	.885**	.773**	.985**	.44	.947**	.936**	.929**	.948**	.818**	–.073
Florence	.891**	.912**	.899**	.661*	.911**	.774**	.782**	.812**	.623*	.301
Venice	.891**	.870**	.955**	.589*	.984**	.841**	.906**	.897**	.752**	.151
Lisbon	.868**	.782**	.978**	.467	.937**	.916**	.893**	.955**	.762**	–.059
Stockholm	.741**	.493	.819**	.183	.834**	.844**	.876**	.866**	.868**	–.316
Brussels	.836**	.829**	.799**	.851**	.722**	.741**	.698*	.630*	.253	.301
Copenhagen	.746**	.481	.808**	.155	.804**	.864**	.855**	.859**	.878**	–.338
Valencia	.824**	.749**	.861**	.552	.941**	.784**	.827**	.854**	.689*	.082
Zurich	.858**	.613*	.903**	.307	.896**	.908**	.930**	.881**	.878**	–.199

Correlations										
City	Hamburg	Budapest	Florence	Venice	Lisbon	Stockholm	Brussels	Copenhagen	Valencia	Zurich
Paris	.889**	.885**	.891**	.891**	.868**	.741**	.836**	.746**	.824**	.858**
Rome	.800**	.773**	.912**	.870**	.782**	.493	.829**	.481	.749**	.613*
Berlin	.981**	.985**	.899**	.955**	.978**	.819**	.799**	.808**	.861**	.903**
Madrid	.522	.44	.661*	.589*	.467	.183	.851**	.155	.552	.307
Barcelona	.963**	.947**	.911**	.984**	.937**	.834**	.722**	.804**	.941**	.896**
Vienna	.923**	.936**	.774**	.841**	.916**	.844**	.741**	.864**	.784**	.908**
Munich	.922**	.929**	.782**	.906**	.893**	.876**	.698*	.855**	.827**	.930**
Amsterdam	.955**	.948**	.812**	.897**	.955**	.866**	.630*	.859**	.854**	.881**
Nice	.749**	.818**	.623*	.752**	.762**	.868**	.253	.878**	.689*	.878**
Milan	–.022	–.073	.301	.151	–.059	–.316	.301	–.338	.082	–.199
Hamburg	1	.980**	.870**	.950**	.976**	.874**	.787**	.857**	.910**	.918**
Budapest	.980**	1	.877**	.946**	.989**	.861**	.709**	.850**	.856**	.935**
Florence	.870**	.877**	1	.939**	.863**	.667*	.747**	.676*	.847**	.802**
Venice	.950**	.946**	.939**	1	.929**	.817**	.733**	.805**	.911**	.886**
Lisbon	.976**	.989**	.863**	.929**	1	.807**	.736**	.788**	.843**	.888**
Stockholm	.874**	.861**	.667*	.817**	.807**	1	.497	.983**	.835**	.946**
Brussels	.787**	.709**	.747**	.733**	.736**	.497	1	.494	.745**	.597*
Copenhagen	.857**	.850**	.676*	.805**	.788**	.983**	.494	1	.804**	.933**
Valencia	.910**	.856**	.847**	.911**	.843**	.835**	.745**	.804**	1	.880**
Zurich	.918**	.935**	.802**	.886**	.888**	.946**	.597*	.933**	.880**	1

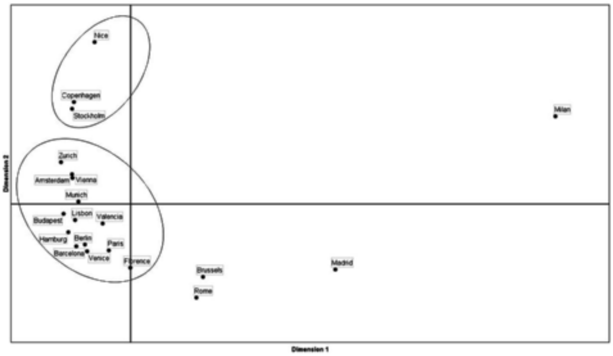
$N = 12$

** $p < 0.01$ level (2-tailed)

* $p < 0.05$ level (2-tailed)

4

Fig. 4 Configuration of destinations' demand patterns similarities (total average bed-nights)



A second, smaller group comprises the three destinations in the top left area of the plot for which tourism demand is concentrated in few months a year. These cities are associated with a distribution with one single peak in the month of August. The presence of a shoulder season explains the distance between Nice and the two Scandinavian destinations. The demand pattern for the French city presents a stark increase and decrease, while that of Copenhagen and Stockholm presents a more gradual increase since the first months of the year.

The remaining points are associated with cities (Milan, Madrid, Brussels and Rome), where the month of August regularly happens to be one of the off-peak months. The reason of this reversed trend can be due to the predominance of business tourists, but also to climatic reasons (especially for Madrid and Rome).

In general, the vertical axis can be interpreted as discriminating destinations in terms of modality of the distribution (uni- versus multi-modal distribution), while the horizontal axis provides hints concerning the importance of the summer season. The results can be used to identify groups of destinations competing in the tourism market at the same times of the year. Interpreting the series of average monthly bed-nights as tourists' preferences to visit a destination in a specific time of the year, the perceptual map reveals the benchmarking partners based on travelers' seasonal behavior rather than on destinations' physical attributes. Within this group, it is evident that Nice's main competitors are not Barcelona and Valencia, which are also located on the shores of the Mediterranean sea, but the two Scandinavian destinations, which attract tourists' at the same period of the year. A similar conclusion can be drawn for Italy's most popular destinations, Venice, Florence and Rome. The capital city of Italy very likely attracts more business visitors than the other two cities of art, which shifts its positioning closer to the country's second largest center for business, Milan.

The same analysis can be performed on bed-night series for individual markets. Such an analysis provides a valid support for country-specific strategies, such as drawing the timeline of marketing activities. As an illustration, the same comparative exercise as above has been performed for two of Europe's most relevant source markets – Germany and the USA. For these countries, the monthly series of bed-nights for the period 2003 to 2007 were available respectively in 13 and 16 of the 20 cities analyzed before. In both cases, the stress values[5] for the two-dimensional configurations were highly satisfactory, and no significant

5 For the German market: 2-dimensions: S-Stress = 0.04, Stress = 0.06; 3-dimensions: S-Stress = 0.01, Stress = 0.02. For the USA market: 2-dimensions: S-Stress = 0.02, Stress = 0.04; 3-dimensions: S-Stress = 0.01, Stress = 0.02.

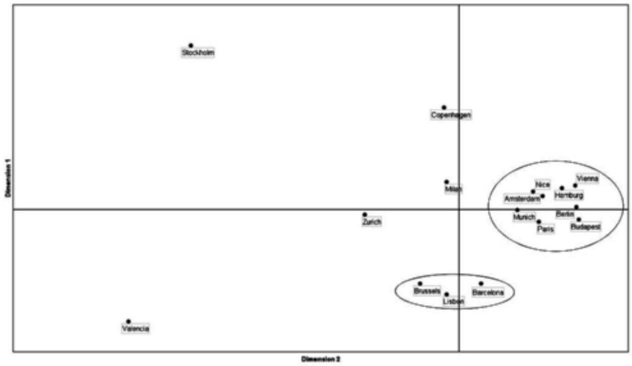


Fig. 5 Configuration of destinations' demand patterns similarities (German average bed-nights)

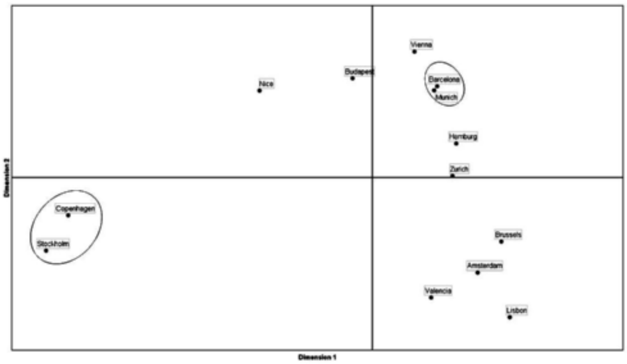


Fig. 6 Configuration of destinations' demand patterns similarities (USA average bed-nights)

improvement could be achieved with an additional dimension.

The outcome of the analysis for the German market is portrayed in Figure 5. In general, German tourists tend to visit the destinations positioned towards the top of the diagram in the summer months, which represent the off-peak period for the cities on the opposite side of the map. The cities in the centre right region of the map (Amsterdam, Berlin, Budapest, Munich, Nice, Paris and Vienna) are characterised by a bi-modal distribution of bed-nights. Among these cities, Berlin, Hamburg and Vienna present a remarkably similar distribution with two seasons, one in month V and a second around month IX.

In the area at the bottom of the map, a second, small group of destinations (Barcelona, Brussels and Lisbon) is also characterised by a bi-modal distribution with the off-peak season in months VI and VII. Not surprisingly, the distribution of bed-nights reveals German's preference for the Scandinavian cities in the summer months, and for the Mediterranean destinations in spring and late summer with the exception of the city of Nice. This comparative exercise highlights a potential for the tourism managers on the French Riviera to consider an increase of the share of the German market[6] as part of a season-extension strategy.

Another interesting example is the analysis of USA demand towards European cities, which is marked by a higher variety of seasonal patterns. The diagram in Figure 6 displays the scattered points representing the USA demand for 13 European cities, which leaves little room for the analysis in isolation of patterns' simi-

6 The German market represents approximately 5% of the total visitors to Nice in the period of reference.

larities. Interpreting the map in the light of the previous results provides more useful, complementary information on destinations' competitive positioning. The positioning of the Scandinavian cities is consistently isolated from the other destinations, which suggests that the major causes of seasonality should reside in pull factors. The cities in the top right panel (Vienna, Barcelona, Munich, Hamburg and Zurich) are characterised by a bi-modal distribution with a peak in June and a second high season around month IX. Among them, Barcelona and Munich present an almost identical pattern in the first 2/3 of the year. In the German market, the situation is significantly different with the two destinations having the demand pattern in the last quarter of the year in common.

4.6 Conclusions

In the analysis of tourism seasonality, two aspects are of particular importance: the "intensity" or amplitude of the phenomenon and the shape of the demand pattern. The assessment of the amplitude of seasonality is relevant for decision-makers in order to prioritise anti-seasonality policies against other types of interventions. The analysis of similarity of demand's pattern is particularly helpful in identifying competitors and interesting markets for season expansion strategies. Instruments suitable for monitoring and benchmarking analysis are a desirable analytical support for developing strategies and policies accounting for the seasonal behavior of the demand.

Seasonality is almost univocally presented as an undesirable facet of tourism, ascribed as the main cause for limited returns on investments, high prices, volatile quality of the service and labour force (Baum and Hagen, 1999). To some extent, seasonality is a manageable aspect, since tourism policy makers and marketers can undertake a set of actions to overcome the monthly fluctuations of demand. Season extension is also a primary goal for city tourism managers and marketers, since a rise in seasonality affects the utilization of resources. Baum and Hagen (1999) identify market and product differentiation and events as destinations' most largely used responses to seasonality in peripheral areas, which are also suitable for urban areas.

Market and product diversification are two very closely related responses, since an effective market differentiation must acknowledge that different seasons create demand for different products. In identifying new markets, which can be attracted by the destination, the benchmarking with competitors is fundamental to tailor effective penetration strategies. The needs and interests of segments capable to travel in off-peak seasons have to be investigated to design the product, the package, price and distribution accordingly. When data on visitors' preferences and attitudes are available, segmentation analyses accounting for seasonal differences can be performed (Calantone and Jotindar, 1984; Snepenger, 1987). Since such information is rarely available for a large number of destinations, competitive analysis based on visitors' past behavior can produce satisfactory results, just as in the examples illustrated in this chapter. Market diversification must be directed to identify new demand for existing products and facilities. Cities rely on a diversified portfolio of attractions, which can be used to develop a seasons-differentiated product mix. The availability of indoor (e. g. museums, galleries or shops) next to outdoor activities (e. g. parks, gardens or markets) needs to be exploited to attract travellers in periods of the year without a good-weather-guarantee. For a product development strategy, cities can also take advantage of the collaboration with peripheral areas marked by a reversed seasonal pattern, exploiting their role as hub for the main forms of transportation.

Events are largely used by cities in the attempt of attracting additional demand. A first coarse distinction can be made between business and leisure events. The potential of the conventions and meeting industry, a fast growing sector, has been recognized by tourism managers, and in Europe, noteworthy investments have been made in conference centers and halls, not only in the capital cities, but also in minor centers. In the area of leisure events, the celebration of theme years is a valuable instrument to generate additional demand in the off-peak periods. Two programs of the European Commission – the Cultural Capital of Europe and the European Destinations of Excellence project (EDEN) – have amongst their objectives that of sustaining European destinations to combat seasonality and rebalance the tourist flows. A joint effort of tourism boards and convention bureaus in promoting the destination is obviously required to avoid the overlapping of the two segments in the same periods, nullifying the effort of implementing anti-seasonal strategies. It is critical for destinations policymakers and marketers to know where to go on a long term basis in order to direct development and marketing strategies towards the achievement of the segment mix that will bring it about (Jang, 2004). A full understanding of the seasonal mechanism and objective assessments of destinations' seasonal profile are a desirable prerequisite of an efficient collaboration.

Web sites of interest

TourMIS – The Marketing Information System for tourism, providing online tourism survey data and decision support for the tourism industry.
http://www.tourmis.info

The European Destinations of Excellence – An initiative of the European Commission to draw attention to the value, diversity and shared characteristics of European tourist destinations, and to promote destinations.
http://ec.europa.eu/enterprise/tourism/major_activities/eu_tourist/index_en.htm

European Capitals of Culture – A series of events, scheduled over one year, through which European cities can promote their cultural richness and diversity. The programme is supported by the European Union Culture programme.
http://ec.europa.eu/culture/our-programmes-and-actions/doc413_en.htm

Vienna Convention Bureau – The Vienna Convention Bureau was set up in 1969 as a department of the Vienna Tourist Board to promote Vienna as Central Europe's leading conference city.
http://www2.vienna.convention.at

Nice Tourism – The official web site of Nice Convention and Visitors Bureau.
http://www.nicetourisme.com

Visit Copenhagen – The official tourism site of Copenhagen and the surrounding area
http://www.visitcopenhagen.com

4

Review questions

(1) The municipality of Nice is planning the enlargement of two infrastructures, the 'Promenade des Anglais' (the famous promenade on the seaside) and the airport. The goal is to enlarge the capacity in order to carry tourism demand at its highest value. Which unit of measurement is more appropriate to measure the carrying capacity for (a) the Promenade and (b) the airport?

(2) The factors generating seasonal variations in demand can be classified as 'pull' or 'push' factors. This aspect of tourism seasonality is referred to as the 'spatial component of seasonality'. Is this aspect peculiar for the tourism industry only, or could this aspect affect other industries too?

(3) Cities as tourism product present specific characteristics, which make them attractive year round. Can these characteristics be reproduced in other types of destinations?

(4) Destinations can provide several responses to the problem of seasonality. Market and product diversification are two measures which are to some extent interdependent. Taking a city destination of your choice, think of a strategy of product differentiation for the destination which would allow attracting one or a few specific market segments in an off-peak period.

(5) In year 2008 the value of the Gini coefficient for the city of Copenhagen was 0.146. Visit the web site www.tourmis.info and compare the result for this city with other city destinations in Europe. How would you evaluate the result of the Scandinavian city?

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