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Quantile Dependence in Tourism Demand Time Series: Evidence in the Southern Italy Market

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Abstract: Travel and tourism is an important economic activity in most countries around the world. In 2018, international tourist arrivals grew 5% to reach the 1.4 billion mark and at the same time export earnings generated by tourism have grown to USD 1.7 trillion. The rapid growth of the tourism industry has globally attracted the interest of researchers for a long time. The literature has tried to model tourism demand to analyze the effects of different factors and predict the future behavior of the demand. Forecasting of tourism demand is crucial not only for academia but for tourism industries too, especially in line with the principles of sustainable tourism. The hospitality branch is an important part of the tourism industry and accurate passenger flow forecasting is a key link in the governance of the resources of a destination or in revenue management systems. In this context, the paper studies the interdependence of tourism demand in one of the main Italian tourist destinations, the Campania region, using a quantile-on-quantile approach between overall and specific tourism demand. Data are represented by monthly arrivals and nights spent by residents and non-residents in hotels and complementary accommodations from January 2008 to December 2018. The results of the analysis show that the hotel-accommodation component of the tourism demand appears to be more vulnerable than extra-hotel accommodation component to the fluctuations of the overall tourism demand and this feature is more evident for the arrivals than for nights spent. Moreover, the dependence on high quantiles suggests strategy of diversification or market segmentation to avoid overtourism phenomena and/or carrying capacity problems. Conversely, dependence on low quantiles suggests the use of push strategies to stimulate tourism demand. Finally, the results suggest that it could be very useful if the stakeholders of the tourism sector in Campania focused their attention on the collaboration theory.

Keywords: tourism demand; time series; quantilogram

1. Introduction

Tourism is indisputably considered a fundamental sector for growth and economic development in both emerging and advanced economies. According to the World Tourism Organization, its contribution in increasing both the quantity and quality of jobs as well as spurring innovation and entrepreneurship is remarkable.

The worldwide success of the tourism sector is irrefutable: In 2018, arrivals grew 5% to reach the 1.4 million mark, and export earnings generated by tourism grew to 1.7 trillion US dollars. In addition, for the seventh consecutive year, tourism exports grew faster than exports of goods, reducing trade deficits in many countries of the world. The success must be traced in a multiplicity of factors among which it is worthwhile to mention the strong global economy, a growing middle class in emerging economies, technological advances, new business models, and affordable travel costs and payments facilitation [1].

The tourism industry has a significant direct economic impact as well as indirect and induced impacts. The total of travel and tourism to GDP (including wider effects from investment, the supply chain, and induced income impacts [2]) was USD 8811.0 billion in 2018 (10.4% of GDP) and is expected to grow by 3.6% to USD 9126.7 billion (10.4% of GDP) in 2019. Travel and tourism has directly generated 122,891,000 jobs in 2018 (3.8% of total employment) and this number is forecasted to grow by 2.2% in 2019 to 125,595,000 (3.9% of total employment). This includes employment by hotels, travel agents, airlines, and other passenger transportation services (excluding commuter services) as well as the activities of the restaurant and leisure industries directly supported by tourists. The total contribution of travel and tourism to employment has been 318,811,000 jobs in 2018 (10.0% of total employment). An increase of 2.9% is expected in 2019 for a total of 328,208,000 jobs, that is 10.1% of total employment [3].

In 2018, Europe accounted for half of the world's international arrivals, followed by Asia and the Pacific (25%), the Americas (15%), Africa (5%), and the Middle East (4%). Moreover, Europe has represented almost 40% of international tourism receipts, followed by Asia and the Pacific with almost one third, the Americas 23%, and then the Middle East (5%) and Africa (3%) (see [1]).

The growth in international tourism has stimulated a remarkable interest in tourism research [4]. Since the end of the World War II, scholars have tried to model the tourism demand [5] to analyze the effects of different factors, and predict the future behavior of demand (see e.g., [6,7]).

These features assume greater importance in a perspective of sustainable tourism [8] in which attention must be paid to the phenomena of "overtourism" and "carrying capacity" which can produce negative effects on the tourist development of the destinations. Thus, the forecasts on tourism demand become crucial not only for academia but also for tourism industries.

The hospitality branch is an important part of the tourism industry and accurate passenger flow forecasting is crucial in the governance of revenue management systems. The hospitality industry, given the structure of the business, is sensitive to fluctuations in demand. The hotel industry may have crises generated by an unexpected reduction in demand; on the other hand, it may be subject to saturation problems due to an unexpected increase in demand. The nature and peculiarities of the accommodation activities suggest paying attention to the forecasting demand. In this sector, often influenced by socio-economic variables, large fluctuations may occur, and it might be necessary to assess the efforts and resources needed to improve the occupancy rate [9].

Accurately forecasting demand is essential in both the public and private sectors [10] for efficient planning by airlines, shipping companies, railways, hoteliers, tour operators, food and catering establishments, and other sectors connected with tourism. Forecasts are also of great interest to governments and national tourist organizations to keep pace with the rapid flow of tourists. From a macroeconomic perspective, destination's infrastructure and promotion require substantial investment and therefore an estimate of the destination's future tourism demand is essential in order to ensure a positive return on investment. If we move to a microeconomic point of view, forecasting tourist demand is an important tool for businesses in the tourism sector, such as airlines, tour operators, hotels, restaurants. Decisions about the price policy and availability or about staffing, purchasing, and budgeting, for example, depend on the accuracy/inaccuracy of data on forecast [11]. Finally, the uncertainty of the passenger flow during the tourist season can cause an overestimate or underestimate of the passenger flow with unavoidable effects in tourism-related industries [12].

Tourism forecasts are also needed in government policy making, especially in countries where economic development depends substantially on tourism [13]. The availability of accurate and timely forecasting of demand is essential for both research and tourism industries (see e.g. [4,14–17]). In order to improve the forecasting accuracy and reduce errors, scholars resort to use of sophisticated data analysis techniques and appropriate datasets, and in addition they try to evaluate the improvement of new methodologies compared to the reference models [18]. In this area, the relevance of online data, such as search engine data, web traffic, social media, and mobile data has been appreciated recently [19,20].

A large amount of literature on tourist demand modeling has been developed over several decades. In general, this literature focuses either on analysis of the effects of the various determinants and/or on the accurate forecasting of tourism demand [4,21], with useful surveys including [22], reviewing more than 300 publications, and [23–26].

The causal relationship between tourist arrivals and influencing factors are explored by econometric models, particularly useful when a linear relationship exists [27,28].

In the past two decades, advanced econometric techniques have had a dominant role in the understanding of tourists' behavior and their demand for tourism products/services. It is possible to classify the large number of empirical studies on international tourism demand into two main groups. The first group consists of studies that estimate the determinants of international tourism demand using classical multivariate regressions, see e.g., [22–25,29]. The second group includes studies that use time series models as well as cointegration techniques (see e.g., [30,31]). Moreover, some authors have explored neural networks methodology [32], fuzzy system approach [33], hybrid forecasting by combining econometric and data mining techniques [34], models based on Markov chains [35] and generalized dynamic factor models [21]. In terms of forecasting accuracy, better results are generally obtained exploiting more advanced methods such as cointegration, error correction model, time-varying parameter model, and their combinations with systems of equations. Moreover, recently, in tourism demand studies, gravity models [36] and panel data approaches [37] have attracted researcher's attention.

A first way to measure tourism demand is to consider the number of arrivals/departures [30,38], but the number of nights spent by tourists and the average length of stay in the destination country (see [39,40]) are also relevant alternatives. However, tourist arrivals and nights spent do not include the consumption behaviors of visitors, so some studies have applied, as a third measurement, the total expenditures made by tourists as a proxy for tourism demand [41–43].

Accurate forecasts of tourist arrivals and room occupancy are certainly fundamental to reach the aim of increasing customers and hotel revenues. Moreover, these forecasts constitute an essential information source to design the demand-side policies pursuing the objective of promoting a more efficient use of resources and the reduction of congestion at peak periods through the reduction of seasonality and increasing the length-of-stay [44]. However, many relevant approaches have the drawback of being mainly intended for large international hotels and hotel chains. In fact, they require detailed data usually disaggregated by customer segment, room type, length-of-stay, and so on. There are many important areas where complementary accommodations are becoming more and more relevant. In these cases, the scarcity of information can definitively reduce the effectiveness of otherwise well-performing models [44].

In this context this paper estimates the quantile dependence of tourism demand in one of the main Italian tourist destinations, the Campania region. The study uses data of arrivals and nights spent by residents and non-residents in hotels and complementary accommodations. The cross-quantilogram method [45,46] is exploited to measure the causal dependence between pairs of stationary variables for different (lower, middle, and upper) quantiles of the distribution. As a result, instead of summarizing the relationship between tourism demand variables through a single number, a nonlinear relationship across a wide range of quantiles is provided. The data have a monthly frequency and cover the period from January 2008 to December 2018.

This study contributes to the empirical literature on tourism demand forecasting by applying for the first time (to the best of our knowledge) the quantile-on-quantile methodology to the Italian tourism context. Secondly, the results on the interdependence analysis of tourism demand and its components can provide useful suggestions for decision making and the competitiveness of the tourism industry. Finally, reliable forecasts of tourism demand can contribute both at macro and micro levels to better planning of tourism activities favoring the positive impact and reducing the negative impact on the tourist destination.

The article is organized as follows. In Section 2 some highlights on tourism in the Campania region are provided. Section 3 focuses on the methodology to study the quantile dependence between two variables and introduces the cross-quantilogram, while Section 4 presents the results of the application to the data of Campania. Section 5 is relative to the discussion and the conclusions are summarized in Section 6.

2. Some Highlights on Tourism in Campania

Campania is a region located in southern Italy and has countless natural, historical-cultural, and gastronomic resources. The tourist destinations include, among others, the city of Naples, Vesuvius, Pompeii ruins, Sorrento, Amalfi coast, Capri and Ischia islands, and Cilento.

In Campania, the tourism industry represents one of the most important economic activities. In 2017 it represented over 4% in terms of added value and over 6% in terms of employees of the total activities (see Table 1). In particular, the percentage of value added has been greater with respect to the southern area (including islands) and Italy.

Table 1. Tourism in Campania, the tourism industry (including classes of accommodation and restaurants) represents value added and persons employed as percentage of total activity, 2017.

	Value Added (%)	Employed (%)
Campania	4.4	6.3
South and Islands	4.2	6.3
Italy	3.9	6.5

Source: Elaboration on ISTAT (Italian National Institute of Statistics) data.

Furthermore, in 2017, among the southern and island regions, Campania shows the highest weights in terms of added value and persons employed, respectively 7% and almost 9%, of national tourism (see Table 2). When the comparison is made with respect to southern Italy, Campania reaches almost 29% and 28%, respectively, for value added and persons employed.

Table 2. Share of tourism value added and persons employed in Italy and in southern Italy, by regions, 2017.

Area	Value Added (%)	Employed (%)	Area	Value Added (%)	Employed (%)
Italy	100	100	Southern Italy	100	100
Abruzzo	1.9	2.6	Abruzzo	7.6	8.2
Apulia	4.7	6.5	Apulia	19.3	20.5
Basilicata	0.6	0.8	Basilicata	2.4	2.5
Calabria	1.9	2.5	Calabria	7.8	8.0
Campania	7.0	8.7	Campania	28.6	27.6
Molise	0.3	0.5	Molise	1.4	1.6
Sardinia	2.9	3.5	Sardinia	11.9	11.0
Sicily	5.2	6.5	Sicily	21.0	20.6

Source: Elaboration on ISTAT data.

In 2018 in Campania there were almost 7200 establishments with over 211,200 beds. The hotel establishments represent 23% of the total with an availability of beds which, however, is prevalent compared to that of the complementary establishments (59% and 41%, respectively).

In the last decade there has been an increase in both the number of facilities (+86%) and the number of beds (+14%). The greatest increase is recorded for the number of complementary facilities (+146%) but this is not, however, reflected in a similar way for beds, since they are generally complementary structures of small dimensions. Therefore, compared to the past, the tourist supply in Campania presents a larger number of hotels and a more widespread extra-hotel sector (see Table 3).

Table 3. Growth rates and weights of tourism capacity in Campania, 2008–2018.

	Hotels and Similar		Complementary Accommodations		Total Accommodations	
	Number	**Beds**	**Number**	**Beds**	**Number**	**Beds**
Change 2008–2018 (%)	3	15	146	11	86	14
Weight 2008 (%)	42	58	58	42		
Weight 2018 (%)	23	59	77	41		

Source: Elaboration on ISTAT data.

The tourist arrivals have been over 6 million and the number of nights spent has been almost 22 million. Considering the accommodation facilities as a whole, between 2008 and 2018, there has been a positive change in tourism both in terms of arrivals (+39%) and nights spent (+16%). In detail, it can be observed that the increase of the international arrivals has been particularly high (+74%). However, it is possible to observe some negative data for nights spent both in general and for the national and foreign component. This indicates that in Campania in the last decade there has been a reduction of the length stay of tourists (see Table 4).

Table 4. Tourism demand growth rates in Campania, 2008–2018.

	Hotels and Similar		Complementary Accommodations		Total Accommodations	
	Arrivals	**Nights Spent**	**Arrivals**	**Nights Spent**	**Arrivals**	**Nights Spent**
	Residents and inbound					
Change 2008–2018 (%)	34	30	77	−20	39	16
	Residents					
	15	13	46	−25	19	1
	Inbound					
	66	55	120	−12	74	37

Source: Elaboration on ISTAT data.

The tourist demand in Campania is still mainly made up by residents, but with a lower weight than ten years ago. International tourism, in fact, currently represents 46% of arrivals and 48% of nights spent (in the past 37% and 41% of arrivals and nights spent, respectively). Table 5 provides some details.

Table 5. Tourism demand weights in Campania.

	Hotels and Similar		Complementary Accommodations		Total Accommodations	
	Arrivals	**Nights Spent**	**Arrivals**	**Nights Spent**	**Arrivals**	**Nights Spent**
	Residents					
Weight 2008 (%)	64	59	59	61	63	59
Weight 2018 (%)	55	51	49	57	54	52
	Inbound					
Weight 2008 (%)	36	41	41	39	37	41
Weight 2018 (%)	45	49	51	43	46	48

Source: Elaboration on ISTAT data.

3. Methodology

The data used to study the interdependence of tourism demand in the area of the Campania are represented by arrivals and nights spent by residents and inbound tourists in hotels and in other tourist accommodations. The sample period spans from January 2008 to December 2018. The data on tourism demand have a monthly frequency and are sourced from the Italian National Institute of Statistics (ISTAT).

Recent studies have highlighted that the analysis of the dependence of two variables can be enriched beyond the estimation and interpretation of the correlation, which is a simple measure of linear relationship, in particular focusing on the relationship between quantiles, that is the so-called quantile dependence [45,46]. The analysis can be limited to a stationary time series with the aim of checking if past quantiles of the time series can help to improve the prediction of future quantiles of the same time series [45]. The purpose can be reached using a new statistical tool, the quantilogram, which is substantially a correlogram of the so-called quantile hits and for this reason it allows to study the directional predictability of a time series. The quantilogram analysis can be extended to a bivariate setting, so that the resulting statistical tool is defined as cross-quantilogram [46]. As a result, the cross-quantilogram can be interpreted as a measure of directional dependence in quantiles of both the variables. In the financial markets literature, further contributions include the analysis of directional dependence from stock market indices to gold prices [47], the study of the intraday directional predictability of some Australian stocks [48], and the investigation of the effect from oil market uncertainty on sovereign credit spreads of oil-exporting countries [49].

In the literature on tourism activity, recent studies have analyzed the quantile dependence between southern European countries (Greece, Italy, Spain, and Portugal) detecting a stronger dependence in tourism activity when markets are growing [50] and have focused on a quantile-on-quantile approach finding out a positive relationship between tourism and economic growth [51].

Let us consider two stationary time series X_t and Y_t, with distribution functions F_X and F_Y. The α-quantile of the two time series are defined, respectively, as $q_X(\alpha) = \inf\{v : F_X(v) \geq \alpha\}$ and $q_Y(\alpha) = \inf\{v : F_Y(v) \geq \alpha\}$ with $0 < \alpha < 1$. The cross-quantilogram is based on the measure of concordance between the binary variables

$$\Psi_{\alpha_X}(X_t - q_X(\alpha_X)) = \begin{cases} 1-\alpha_X & if \quad X_t \leq q_X(\alpha_X) \\ -\alpha_X & if \quad X_t > q_X(\alpha_X) \end{cases}$$

and

$$\Psi_{\alpha_Y}(Y_t - q_Y(\alpha_Y)) = \begin{cases} 1-\alpha_Y & if \quad Y_t \leq q_Y(\alpha_Y) \\ -\alpha_Y & if \quad Y_t > q_Y(\alpha_Y) \end{cases}$$

also known as quantile hits.

The cross-quantilogram is then estimated as the cross-correlation of the quantile hits variables, $\Psi_{\alpha_X}(X_t - q_X(\alpha_X))$ and $\Psi_{\alpha_Y}(Y_t - q_Y(\alpha_Y))$, that is

$$\hat{\rho}_{\alpha_X,\alpha_Y} = \frac{\sum_{t=1}^{T} \Psi_{\alpha_X}(X_t - q_X(\alpha_X))\Psi_{\alpha_Y}(Y_t - q_Y(\alpha_Y))}{\sqrt{\sum_{t=1}^{T}[\Psi_{\alpha_X}(X_t - q_X(\alpha_X))]^2}\sqrt{\sum_{t=1}^{T}\left[\Psi_{\alpha_Y}(Y_t - q_Y(\alpha_Y))\right]^2}}$$

It can be easily shown that $-1 \leq \hat{\rho}_{\alpha_X,\alpha_Y} \leq 1$. If $\hat{\rho}_{\alpha_X,\alpha_Y} = 0$, there is no directional predictability, that is the knowledge to be below (or over) a certain quantile for a time series does not help to improve the prediction of the other time series. In presence of $\hat{\rho}_{\alpha_X,\alpha_Y} > 0$, when time series X_t is below (over) its quantile $q_X(\alpha_X)$, then time series Y_t tends to be below (over) its quantile $q_Y(\alpha_Y)$; finally, when $\hat{\rho}_{\alpha_X,\alpha_Y} < 0$, the reverse holds, that is when time series X_t is below (over) its quantile $q_X(\alpha_X)$, then time series Y_t tends to be over (below) its quantile $q_Y(\alpha_Y)$;.

The (static) equation of $\hat{\rho}_{\alpha_X,\alpha_Y}$ can be easily extended in a dynamic version when the two time series are not considered at the same time, but a lag k separates them. In this case we can define

$$\hat{\rho}_{\alpha_X,\alpha_Y}(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha_X}(X_t - q_X(\alpha_X))\Psi_{\alpha_Y}(Y_{t-k} - q_Y(\alpha_Y))}{\sqrt{\sum_{t=k+1}^{T}[\Psi_{\alpha_X}(X_t - q_X(\alpha_X))]^2}\sqrt{\sum_{t=k+1}^{T}\left[\Psi_{\alpha_Y}(Y_{t-k} - q_Y(\alpha_Y))\right]^2}}$$

with $k = \pm 1, \pm 2, \ldots$

This type of analysis is able to provide a complete picture of the relationship between two variables, especially when fine grids for α_X and α_Y are taken into account which implies that a high number of quantiles is considered.

Moreover, it does not require any distributional assumptions (see e.g., [46]).

The results can be effectively visualized using a heatmap. A heatmap is a graphical tool that can describe the whole bivariate distribution of two variables in a very detailed manner, making use of a set of colors to represent different values. In particular, the heatmap reports the values of $\hat{\rho}_{\alpha_X,\alpha_Y}$ or $\hat{\rho}_{\alpha_X,\alpha_Y}(k)$ for different values of α_X and α_Y measured on the x-axis and y-axis, respectively. The heatmap provides a full description of the quantile dependence of the variables. It allows to detect the relationship between low quantiles of X_t and low/high quantiles of Y_t, as well as between high quantiles of X_t and low/high quantiles of Y_t.

4. Results

The results of the analysis are presented separately for arrivals and nights spent.

4.1. Arrivals

The time series of the total number of Italian arrivals is represented in the top of Figure 1, while the time series of hotel accommodation and extra-hotel accommodation arrivals are in the middle and bottom part. The expected seasonal component is evident. In order to study the relationship between total arrivals and hotel accommodation arrivals first, and total arrivals and extra-hotel accommodation arrivals, we have removed the seasonal component. The three series have been filtered using, respectively, ARIMA(1,0,1)x(0,1,1), ARIMA(1,0,1)x(1,1,1), and ARIMA(0,0,1)x(0,1,0) models, which stress the presence of a nonstationary seasonal component in all the cases.

In Figure 2, the time series of the total number of foreign tourist arrivals is depicted in the top part while the partition in hotel accommodation and extra-hotel accommodation arrivals can be visualized in the middle and bottom part. For the three time series, ARIMA(2,0,0)x(0,1,1), ARIMA(1,0,0)x(0,1,1), and ARIMA(1,0,1)x(0,1,0) models, respectively, have been estimated to remove the nonstationary seasonal component.

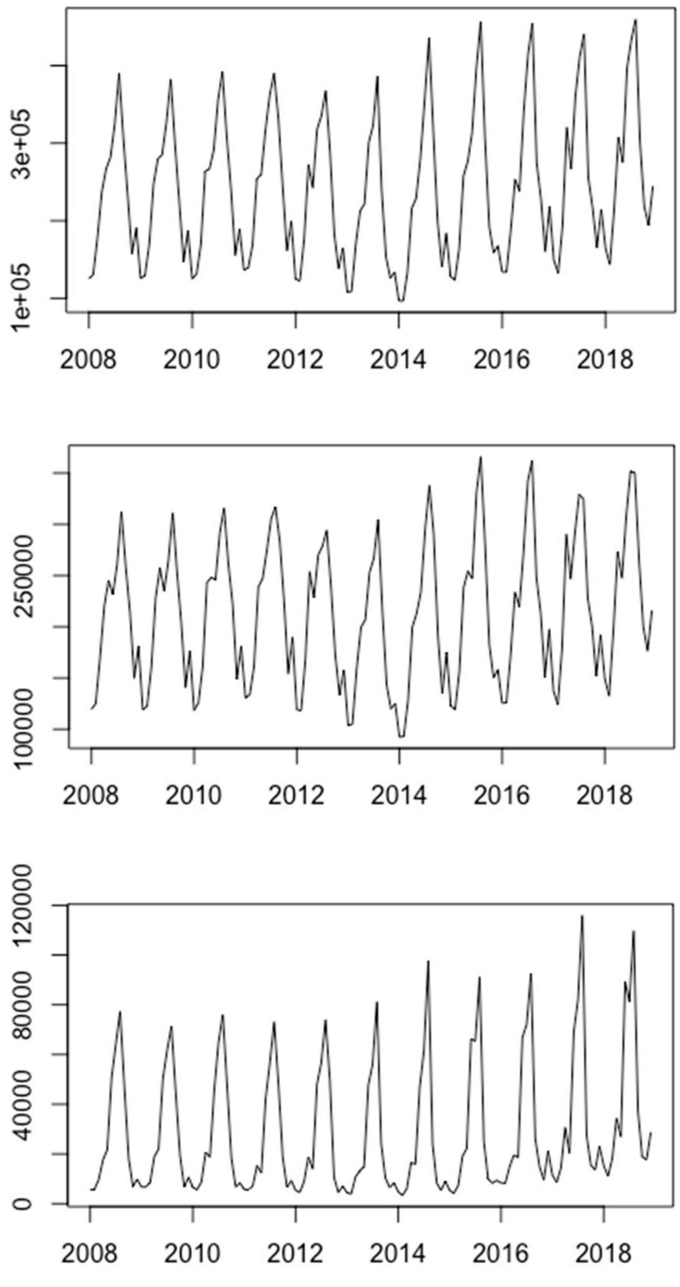

Figure 1. Total arrivals (**top**), hotel accommodation arrivals (**middle**), extra-hotel accommodation arrivals (**bottom**), Italian tourists, monthly data, 2008/01–2018/12.

The cross-quantilograms have been built considering 99 equispaced quantiles (from the first to the 99th percentile) for a total of 9801 estimates $\hat{\rho}_{\alpha_X,\alpha_Y}$.

The first cross-quantilogram (top of Figure 3) shows the relationship between the quantiles of the total number of resident tourist arrivals and the number of resident tourist arrivals selecting hotel accommodation. The net concentration of high values of the cross-quantilogram on the main diagonal is a signal of high dependence when we consider the same quantiles. Moreover, the high values tend to be present more in the lower tail than in the upper tail. So, when the number of arrivals of Italian tourists is low (e.g., the variable arrivals is lower than the 10th quantile) then the number of arrivals in hotels is strongly dependent ($\hat{\rho}_{\alpha_X,\alpha_Y} \approx 1$), that is low as well. On the other hand, when we observe a value in the upper tail (e.g., the variable arrivals is greater than the 80° quantile) then the dependence of the arrivals to hotel accommodations is positive and between 0.50 and 0.80. The bottom part of Figure 3 shows the cross-quantilogram considering the total number of resident tourist arrivals and the number of resident tourist arrivals to complementary establishments. The picture is clearly different. Now we observe values around 0.60 only in the extreme lower tail. In the rest of the diagram the values denote a small positive dependence. The upper quadrant is almost similar, so the main difference between hotel and extra-hotel accommodation figures lies in the area close to the diagonal approximately from the 70° percentile going down.

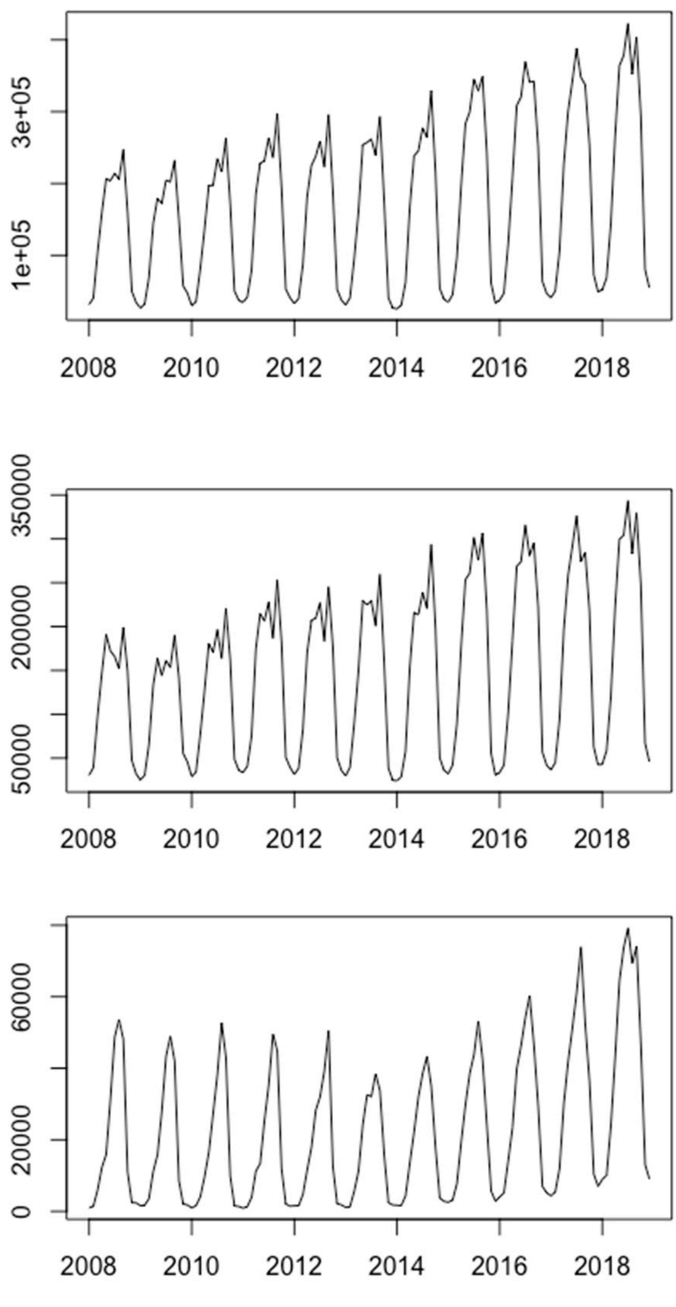

Figure 2. Total arrivals (**top**), hotel accommodation arrivals (**middle**), extra-hotel accommodation arrivals (**bottom**), foreign tourists, monthly data, 2008/01–2018/12.

In Figure 4 the cross-quantilograms reported for foreign tourists show some similarities. When we focus on hotel accommodation, we detect strong relationships along the main diagonal, while the heatmap drawn for the foreign tourists selecting extra-hotel accommodation shows values around 0.60 when the two percentiles are approximately between 0.60 and 0.80.

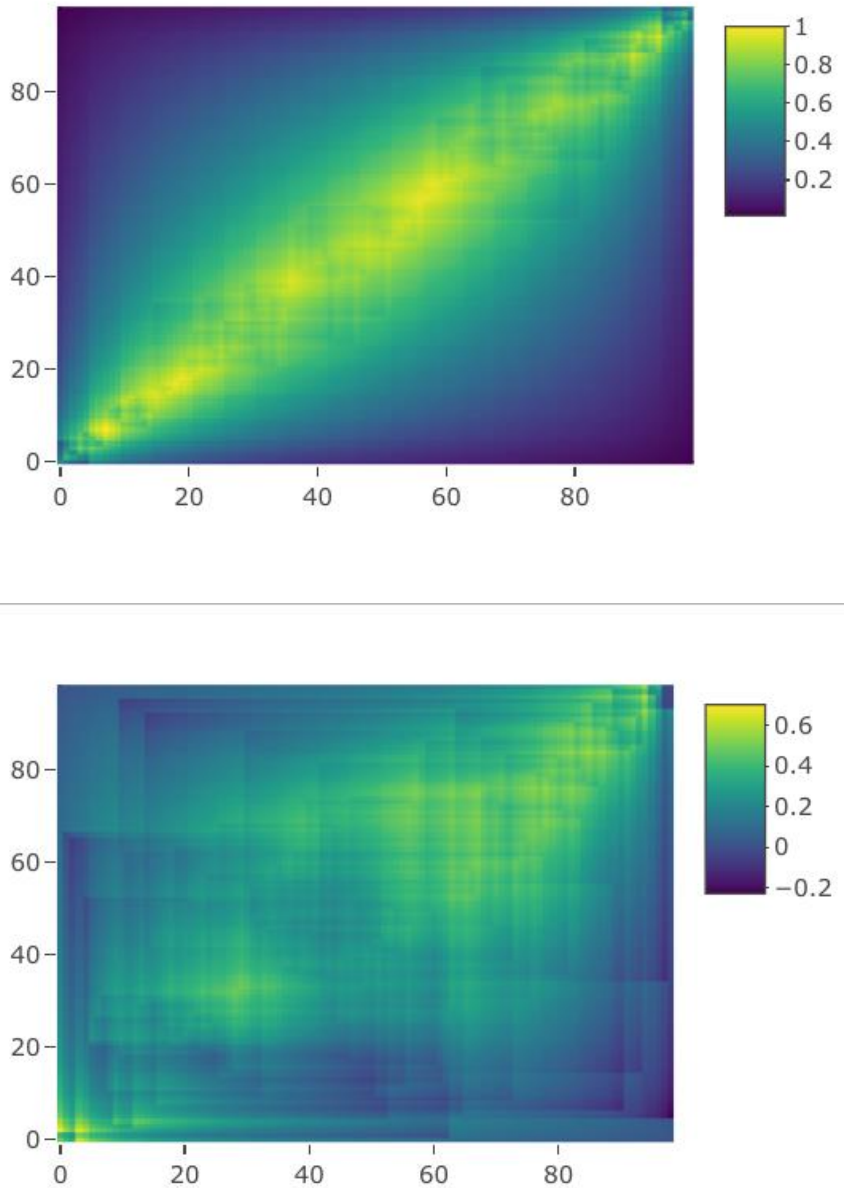

Figure 3. Cross-quantilogram between total arrivals (horizontal axis) and hotel accommodation arrivals (**top**), and between total arrivals (horizontal axis) and extra-hotel accommodation arrivals (**bottom**), Italian tourists.

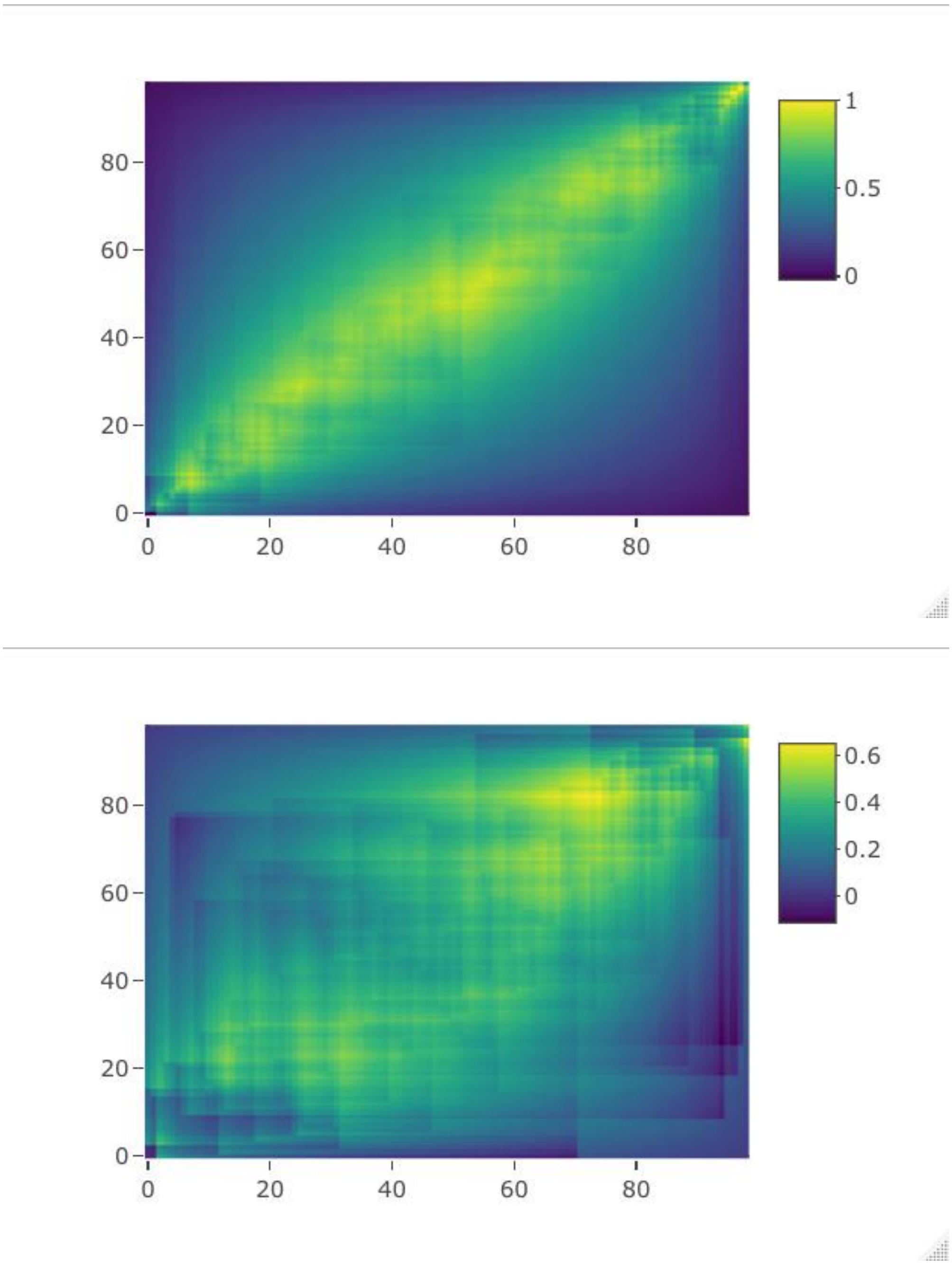

Figure 4. Cross-quantilogram between total arrivals (horizontal axis) and hotel accommodation arrivals (**top**), and between total arrivals (horizontal axis) and extra-hotel accommodation arrivals (**bottom**), foreign tourists.

4.2. Nights Spent

Figure 5 shows the total number of nights spent by Italian tourists (top of the figure), the number of nights spent in hotel accommodation (middle of the figure), and the number of nights spent in extra-hotel accommodation (bottom of the figure). A seasonal component is again easily detected. In order to remove it in the three time series, we have estimated, respectively, ARIMA(1,0,1)x(0,1,1), ARIMA(1,0,0)x(0,1,1), and ARIMA(1,0,0)x(0,1,0) models.

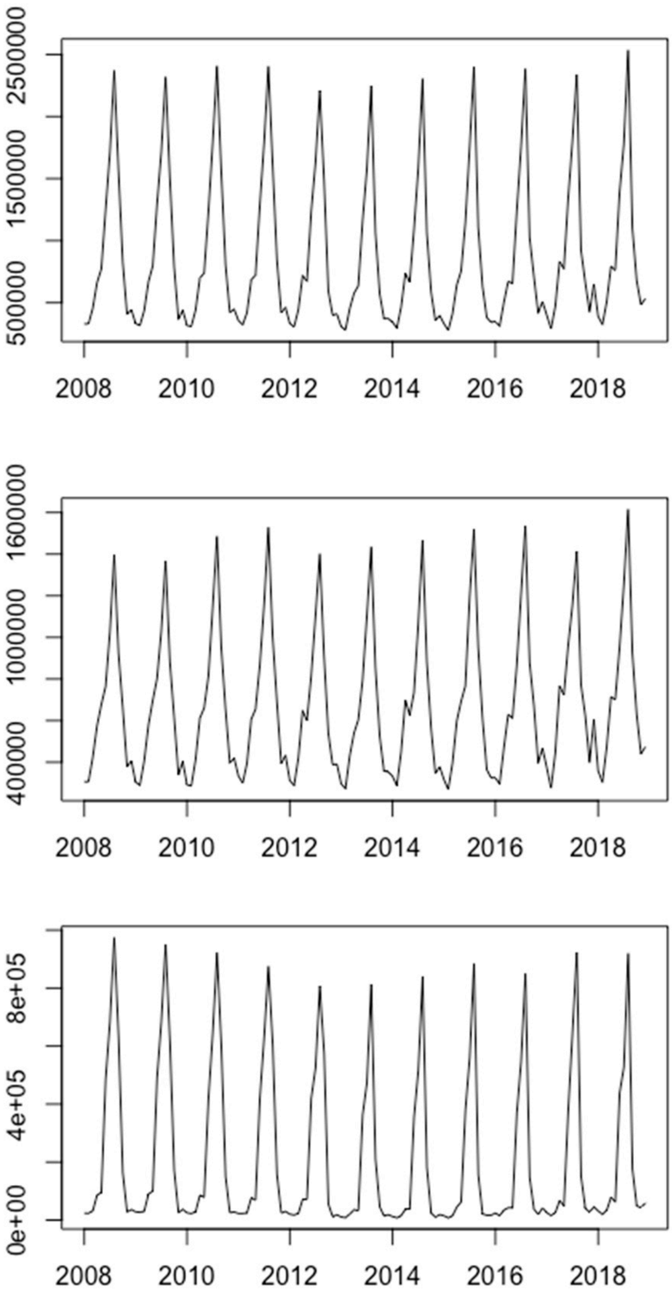

Figure 5. Total nights spent (**top**), hotel accommodation nights spent (**middle**), extra-hotel accommodation nights spent (**bottom**), Italian tourists, monthly data, 2008/01–2018/12.

In Figure 6 the time series of the number of nights spent by foreign tourists (total, selecting a hotel accommodation and selecting an extra-hotel accommodation) are reported. The characteristics are similar to the other time series, apart from the last series, which shows lower values since 2013. The seasonal components have been removed after applying, respectively, ARIMA(1,0,1)x(0,1,1), ARIMA(1,0,0)x(2,1,0), and ARIMA(1,0,0)x(0,1,0) models.

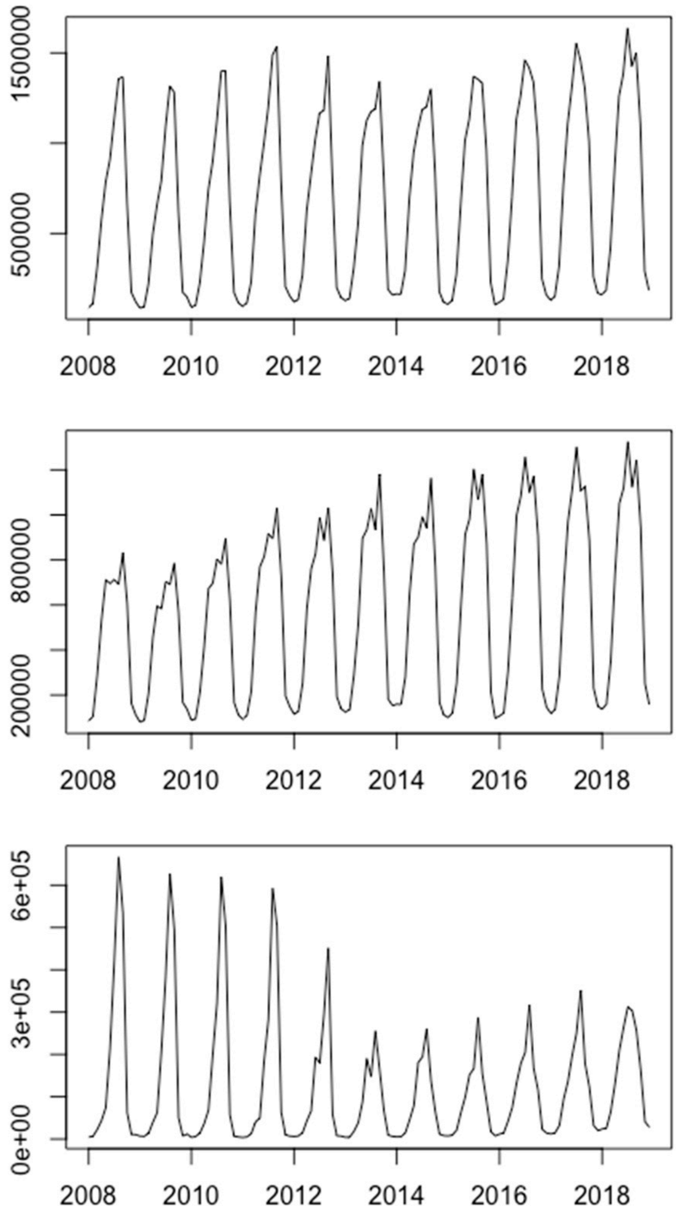

Figure 6. Total nights spent (**top**), hotel accommodation nights spent (**middle**), extra-hotel accommodation nights spent (**bottom**), foreign tourists, monthly data, 2008/01–2018/12.

The cross-quantilograms have been built considering the same 99 quantiles. The first cross-quantilogram (top of Figure 7) shows the relationship between quantiles of the total number of resident tourist nights spent and the number of resident tourist nights spent selecting a hotel accommodation. The presence of stronger relationships is evident when we focus on the quantiles referring to the area close to the main diagonal, but to a less extent with respect to the arrivals time series. The bottom quantilogram is focused on the extra-hotel accommodation and shows high values only in the extreme part of the bottom-left quadrant.

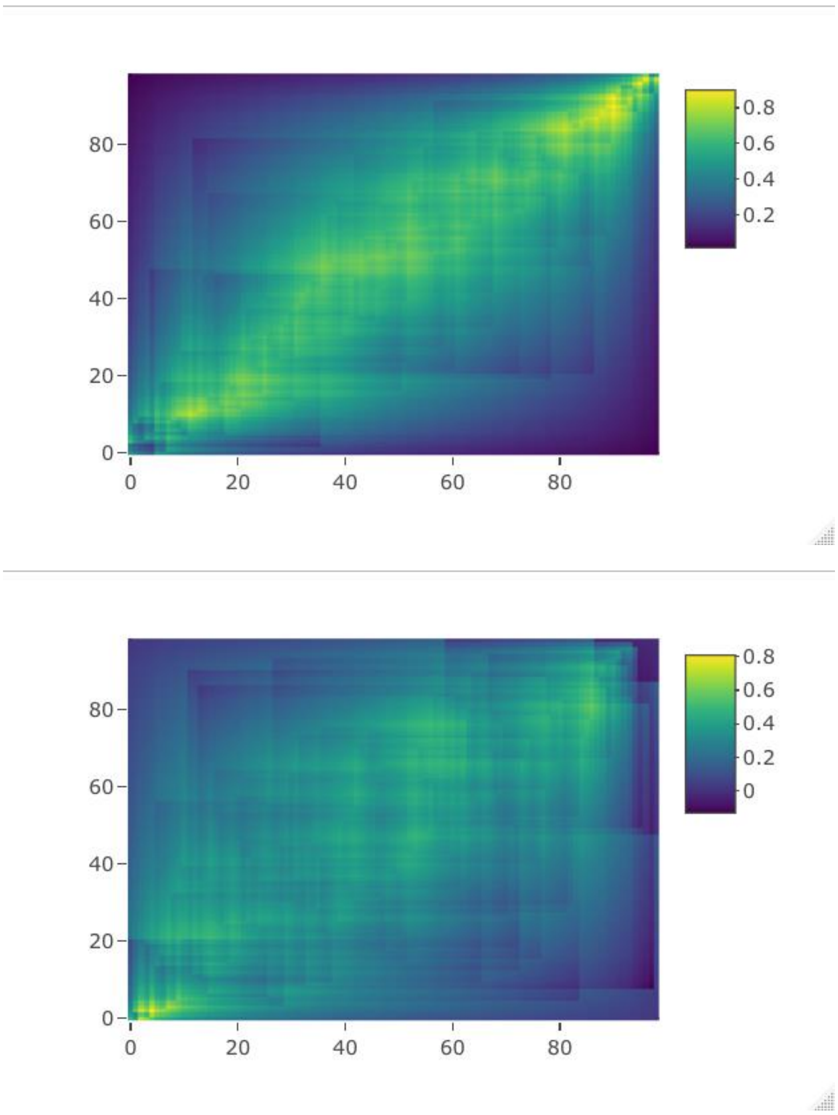

Figure 7. Cross-quantilogram between total nights spent (horizontal axis) and hotel accommodation nights spent (**top**), and between total nights spent (horizontal axis) and extra-hotel accommodation nights spent (**bottom**), Italian tourists.

Finally, the analysis of Figure 8 allows to evaluate for foreign tourists the relationship between total nights spent and hotel accommodation nights spent (top), and total nights spent and extra-hotel accommodation nights spent (bottom). In the top part high values are observed in the band near the main diagonal while in the bottom part weaker associations are detected apart for very small quantiles.

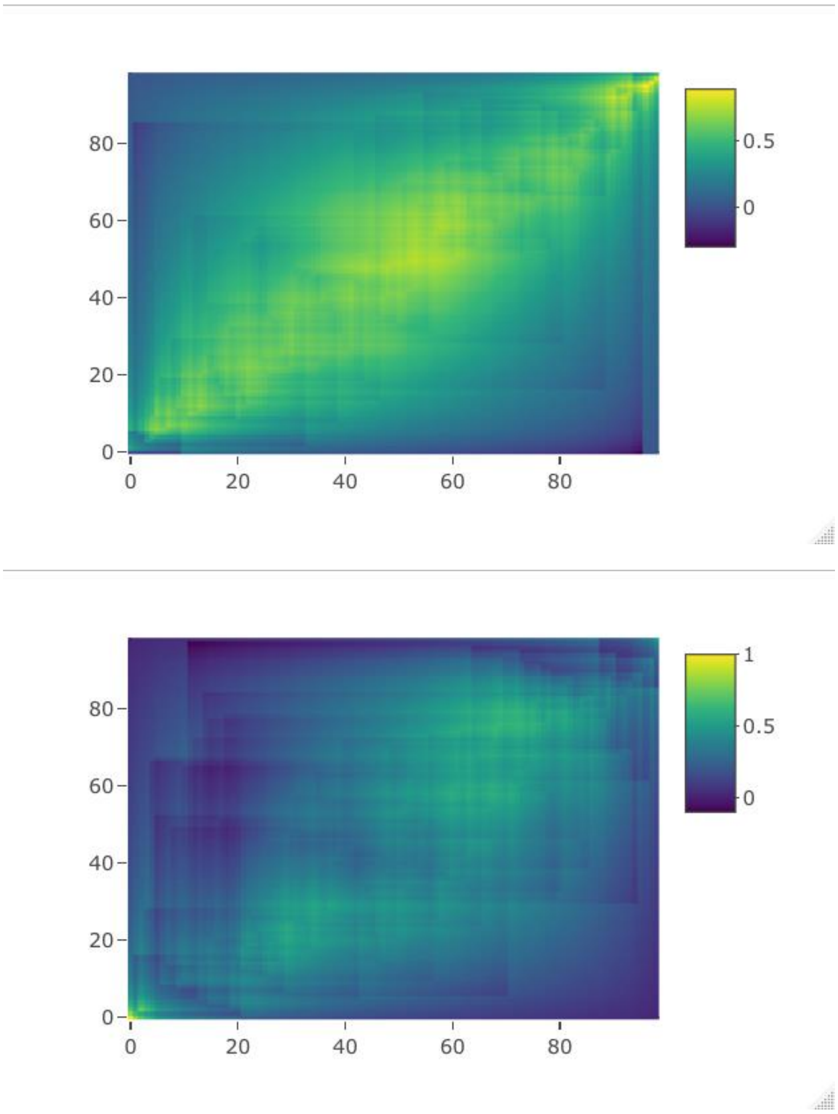

Figure 8. Cross-quantilogram between total nights spent (horizontal axis) and hotel accommodation nights spent (**top**), and between total nights spent (horizontal axis) and extra-hotel accommodation nights spent (**bottom**), foreign tourists.

5. Discussion

Similar to other empirical application of the cross-quantilogram approach [50,51], for Campania tourism this methodology appears as a useful tool for analyzing tourism demand.

From the interpretation of the results a main consideration emerges: The dependence between the time series examined is certainly evident. In detail, when analyzing tourism arrivals, a high dependence between the overall demand and the hotel demand emerges both for residents and non-residents. This evidence is replicated for extra-hotel arrivals, especially for left tail events.

A dependence relationship is also observed for nights spent, even if the association is less marked with respect to the arrivals and substantially focused on lower quantiles. Furthermore, the dependence relations appear rather blurry for the international demand.

In synthesis, the two components of the tourism demand are sensible to fluctuations of the overall tourism demand; in particular, hotel demand can be deemed more vulnerable than extra-hotel demand and this is more evident for the arrivals than for the nights spent.

This evidence suggests the following considerations. First, the hotel industry needs to pay more attention to forecasting on resident and international tourism demand, because variations in tourism demand imply similar fluctuations in hotel occupancy rate. The dependence on both the tail events recommends different behaviors. For the high quantiles a diversifications strategy or a segmentation of the market appears appropriate; conversely, the dependence in lower quantiles could suggest the implementation of push strategies to increase the attraction towards the tourist destination. Furthermore, considering similar behavior in complementary establishments, it could be interesting for the tourism industry to resort to collaborative marketing strategies or collaborative planning efforts, in other words apply the principles that characterize the so-called multi-sector collaboration [52]. This feature assumes even greater importance if we consider the increase (+77% in terms of arrivals) recorded in extra-hotel demand in recent years.

Secondly, the results about nights spent suggest that it could be useful to implement strategy based on the control of maximum/minimum length of stay. The knowledge of the behavior of the arrival and nights spent hotel and extra-hotel demand in relation to the overall tourism demand is useful also for considerations about the immediate or lasting economic, environmental, socio-cultural impact of tourism on the destination, that is on the sustainable development of the tourism destination.

So, the theoretical importance of the paper can be found in having added a piece in the usefulness of applying the rather recent cross-quantilogram approach to the socio-economic context. Besides, the paper contributes to the tourism forecasting demand assigning importance to all values of the series, not only to the average values.

In a future perspective, the path followed in this paper to analyze the tourism demand could be expanded, for example, considering different temporal lag, comparing different tourism destinations or, conditionally on the availability of the data, other tourism demand components.

6. Conclusions

The increase of tourism around the world and the need to adopt sustainable tourism development strategies point out that accurate tourism demand forecasts are indispensable. For these reasons, each contribution beyond standard statistical analysis is particularly useful.

In this study the cross-quantilogram approach has been applied to the time series of tourism demand in Campania, the main destination of southern Italy. In detail, the paper analyzes the relationship between the total tourism demand and the hotel tourism demand, as well as between the total tourism demand and extra-hotel demand, in the last ten years. The analysis has been carried out for arrivals and nights spent and also for residents and international tourists.

The application of the cross-quantilogram methodology has highlighted a remarkable dependence between the time series analyzed such that interesting issues have emerged about sustainable tourism development strategies.

The interesting results of the analysis encourage to proceed in other applications of the cross-quantilogram approach in the tourism sector. In a future perspective it could be interesting searching for the dependence considering different temporal lags, or different tourism destinations or other tourism demand components.

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