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Is hotel revenue performance effective for destination competitiveness? An assessment by wavelet coherence analysis

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Abstract
Hotel industry is crucial for destination competitiveness as part of quality tourist infrastructure. The high performance of the industry promises a positive effect on destination competitive. This study aims to develop a approach focusing on the hotel revenue-related performance data in the case of European cities (Istanbul, London, Madrid, Paris, and Rome). Wavelet coherence analysis was applied on revenue data of the years 2013–2022 from 4000+ hotels. Findings reveal time–frequency relationships between hotel revenue variables, highlighting consistent coherence in supply–demand relationships during the pandemic, except for Rome. Furthermore, the analysis detected differentiated patterns in supply–revenue coherence, with Istanbul's market showing unique fluctuations. London is the city with higher revenue expertise. Key revenue performance indicators of hotels emerged as significant determinants of a city's competitiveness. These insights present implications for policymakers, community stakeholders, and industry practitioners, emphasizing the pivotal role of adept revenue professionals in improving competitiveness in their destinations.

Keywords Wavelet coherence analysis · Destination competitiveness · Revenue management · Hotel industry

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1 Introduction

Destination competitiveness (DC) is a complex and dynamic concept (Altınay and Kozak 2021), which includes factors of the macro and microenvironment to create a comparative advantage for countries (Dwyer and Kim 2003). As a part of the microenvironment, this concept also encompasses the multi-faceted role of the lodging industry in a destination (Assaf et al. 2015; Chin et al. 2017; Manrai et al. 2020). The complex, dynamic, and multi-dimensional nature of the competitive landscape requires sophisticated and analytical methods to assess the competitive performance of destinations, which remains a critical subject (Avila-Robinson and Wakabayashi 2018; Binesh et al. 2023). Given the essence of competitiveness based on the economic prosperity of countries, economic terms such as price competitiveness and productivity of services and establishments play a vital role for DC (Dwyer and Kim 2003; Enright and Newton 2004; Fernández et al. 2020; Park and Jang 2014; Tsai et al. 2009).

Lodging and hotel businesses take part in the tourist services infrastructure as one of the most effective determinants of DC (Enright and Newton 2004; Fernández et al. 2020; Park and Jang 2014). Given the critical role of prices for competitiveness and demand increase in a destination (Malasevska et al. 2020) and especially to drive competitive advantage in crisis periods (Singh and Corsun 2023), revenue management (RM) related metrics appear as suitable measurement variables. Key performance indicators (KPIs) such as supply and demand trends, average daily rates (ADR), occupancy (OCC), and revenue per available room (RevPAR) can be included in various relational analyses to conduct an extensive competitive analysis of the urban markets (Madanoglu and Ozdemir 2016; Chattopadhyay and Mitra 2019). The use of KPIs is effective for the assessment of tourism and hotel competitiveness based on the emphasis on productivity, performance measurement, quality, pricing, and value perception (Tsai et al. 2009). The use of such metrics within a dynamic and large volume of data offers fruitful grounds for sophisticated methods such as Wavelet Coherence Analysis (WTC).

This study aims to develop a more focused approach for DC based on the hotel RM data in the case of European city destinations by assessing the competitiveness of major European cities using WTC. The paper focuses on five prominent European cities as per their urban tourism potential: Istanbul, London, Madrid, Paris, and Rome. The principal reason for selecting certain cities was their position to attract the highest numbers of tourists in the first five countries in Europe. The cities are considered among the first 20 in the world and first 10 in Europe as the best cities for locals, visitors, and businesspeople (Resonance 2023). UNWTO (2022) data states that France, Spain, Türkiye, Italy, and the United Kingdom are the first five countries to attract the highest numbers of tourists in the European region. Those cities are also placed in top cities globally (Euromonitor 2022; TripAdvisor 2023). Figure 1 shows the tourism and accommodation potential of these countries.

As seen in Fig. 1, the COVID-19 effects are evident with a sharp decrease in tourist numbers and tourism receipts in 2020 and 2021, with a slight recovery in 2022 as also observed in tourism stock market (Kalinowski 2024). Spain was the country with the highest tourism income before the pandemic and lost its place to the UK. The UK showed an interesting curve with the highest income per tourist despite the lowest number of tourists in 2021. Türkiye was the country with the lowest room capacity in 2013 but doubled that capacity by 2022. Four countries are close to each other in terms of

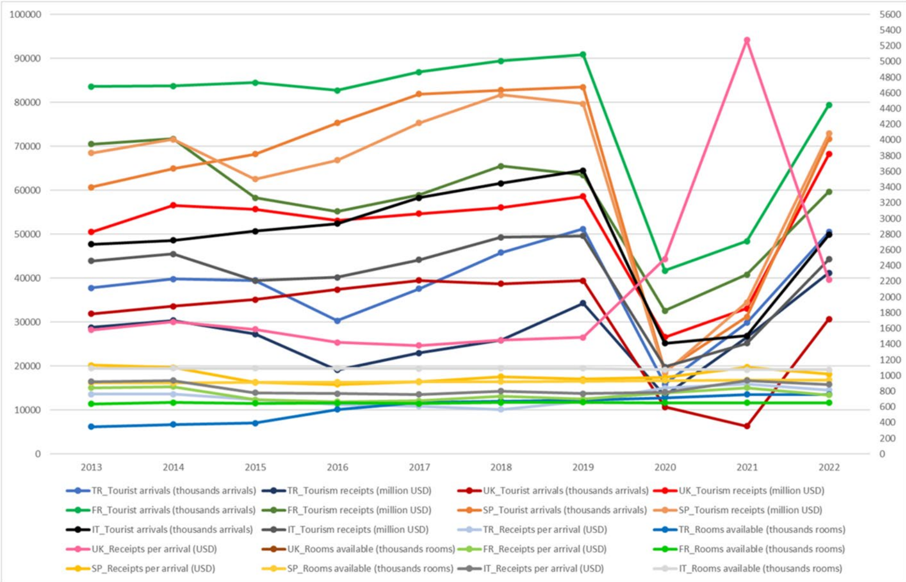


Fig. 1 Tourism and accommodation potential of countries in the research. *Source*: UNWTO (2023). Dashboard. https://www.unwto.org/tourism-data/global-and-regional-tourism-performance

receipts per arrival; however, the UK has recorded a remarkable performance compared to other countries throughout the 10-year period.

Although global tourism statistics offer a comprehensive view on major European destinations, more sophisticated methods of processing longitudinal data generate insightful findings for policy development and strategic plans in specific industries. On the one hand, hotels are considered as key stakeholders in destinations (Sheenan and Ritchie 2005) and revenue practices in hotels are critical for RM in destinations (Kuokkanen and Bouchon 2021). On the other hand, crises such as COVID-19 cause severe decline in hotel revenue forecasts with crucial effects on destinations (Gössling et al. 2020).

This study distinguishes itself from previous research on DC by employing WTC to hotel RM data, an innovative method not previously utilized in this context. Unlike earlier studies that primarily used traditional statistical methods or qualitative assessments, this research captures both linear and non-linear relationships over a decade-long period (2013–2022), providing a more detailed and dynamic understanding of DC dynamics. For example, while Richards and Wilson (2004) examined the impact of cultural events on city images, Maitland and Newman (2014) compared the attractiveness of cities for cultural tourists using conventional methodologies. In addition, Lew and McKercher (2006) compared tourist movement patterns, and Vanolo (2008) examined the role of urban regeneration in enhancing DC. This study with a focus on accommodation metrics leverages the current DC frameworks and utilizes advanced capabilities of WTC to uncover intricate time–frequency relationships in RM data.

By focusing on five major European cities—Istanbul, London, Madrid, Paris, and Rome—this research not only compares these key tourism hubs but also assesses their performance in response to significant events, such as the COVID-19 pandemic, thus addressing both crisis periods and recovery phases. Moreover, this study contributes to ongoing practical debates in the European tourism field, particularly in enhancing competitiveness and resilience amid global challenges. Current discussions emphasize the need for robust strategies to sustain tourism competitiveness and adapt to crises. By demonstrating how sophisticated RM strategies can bolster a city's competitive position and mitigate the adverse impacts of crises, this research provides actionable insights for policymakers and industry stakeholders. Those findings are particularly relevant for urban tourism development, strategic planning, and the application of advanced analytical methods to tourism studies, thus offering practical implications for enhancing the resilience and sustainability of the tourism industry in Europe.

The use of WTC as an analysis method to assess the DC introduces a new and focused perspective focusing on hotel performance data. WTC is a method that has been used extensively in economic analyses (Grinsted et al. 2004) which can identify both linear and non-linear relationships between variables across different time periods. To the best of researchers' knowledge, WTC is a new methodology applied in the tourism field and the first in the DC context. The method was utilized in the study of Zaki (2022), who assessed the RM practices in the pandemic period. The current study benefits from the strength of WTC to analyze (non)-linear relationships among multiple metrics in a long-time span to bring a new perspective of DC based on hotel RM data.

In addition to the methodological novelty, this study significantly contributes to the understanding of DC by providing comprehensive empirical evidence on how hotel RM metrics influence DC. By analyzing a large dataset of over 4000 hotels across five major European cities (Istanbul, London, Madrid, Paris, and Rome) from 2013 to 2022, the research reveals intricate time–frequency relationships between KPIs such as ADR, OCC, RevPAR, and supply–demand dynamics. These findings offer practical insights for policymakers and industry stakeholders, demonstrating how effective RM strategies can enhance a city's competitive edge in the tourism market. Moreover, the study highlights the role of sophisticated RM practices in mitigating the adverse impacts of crises like the COVID-19 pandemic, providing a valuable framework for improving resilience and sustainability in urban tourism. This research not only advances the theoretical framework of DC but also offers actionable insights that can inform strategic planning and policy formulation aimed at boosting tourism competitiveness.

Furthermore, the current study extends the theoretical framework of DC by integrating sophisticated analytical techniques like WTC to unravel the complex interplay between hotel revenue performance and DC. It contributes new knowledge by demonstrating the empirical relevance of hotel revenue indicators as critical determinants of a city's competitive edge in the tourism sector, thereby enriching the existing theoretical discourse on urban tourism competitiveness. This paper is intended for academics, policymakers, tourism industry practitioners, and RM professionals seeking to understand and enhance DC. The insights are particularly valuable for those involved in urban tourism development, strategic planning, and the application of analytical methods to tourism studies.

2 Literature review

DC remains a pivotal concept within tourism studies, focusing on the capacity of a destination to attract and satisfy tourists effectively. The fundamental definition of DC refers to the ultimate advantage of attracting the highest number of tourists leading to an increase in market share, receipts, and the welfare of the local people (Tsai et al. 2009). DC is a complicated framework that includes a wide range of indicators, including micro and macro environment, situational, supporting, demand- and market-related factors, in addition to resources and management policies (Dwyer and Kim 2003). Several business-related factors, such as commercial activities, market potential, international access, local firms' strategies, and quality are also effective (Enright and Newton 2004). The complexity of the DC is also examined by the Butterfly Competitiveness Model (Altınay and Kozak 2021) which emphasizes the dynamic and non-linear interactions within the tourism sector that can lead to significant changes in a destination's competitiveness. That research grounded on chaos theory also suggests that minor changes in one aspect of the tourism system can significantly impact overall DC.

Assaf and Tsionas (2015) rank tourism destinations based on their technical efficiency (accommodation capacity, capital investment) and destination quality (natural, human resources, infrastructure). Vargo and Lusch (2016) extend the service-dominant logic to tourism, proposing that competitiveness is increasingly determined by the co-creation of value between tourists and service providers. This perspective encourages destinations to focus on interactive experiences and personalized services as key components of their competitive strategy. Gómez-Vega and Picazo-Tadeo (2019) extend DC from worldwide tourism performance to a wider perspective including economic, geographical, cultural and political features. Richards and Marques (2019) explore the rising trend of creative tourism, where destinations attract tourists through unique, culturally enriching experiences that cater to evolving consumer preferences. This trend is closely analyzed by Tur Mari (2019), who emphasize the increasing demand for authentic and memorable tourism experiences, thus influencing DC through experiential supply.

In the following years, current global and innovative considerations were incorporated to DC-related research. Gretzel et al. (2020) discuss the significant impact of digital transformation on tourism, highlighting the advent of smart tourism and its role in enhancing DC by improving tourist experiences through technology. Concurrently, sustainability issues, as discussed by Buckley (2020) underscores the necessity for destinations to adopt sustainable practices to mitigate environmental impacts and enhance their long-term attractiveness and viability.

3 Hypotheses development

Despite extensive literature on various aspects, DC-related research remains a promising ground for future studies given the indispensable orientation of destinations for a higher competitive advantage and market share (Cronjé and du Plessis 2020). In addition, the dynamic capabilities perspective, as discussed by Camisón and Monfort-Mir (2012), underlines the critical importance of accurately measuring innovation in the tourism industry to maintain competitive advantage. The paper highlights the need for improved methodologies that reflect the unique and diverse innovation activities of tourism firms, enabling them to better adapt to evolving market demands. By integrating Schumpeterian theory and dynamic capabilities approaches, the proposed innovation scoreboards could help firms align more closely with contemporary tourist expectations and demands.

A new perspective based on accommodation capabilities offers the potential to refine DC assessment framework given the critical determinant role of the lodging and hotel businesses (Enright and Newton 2004; Fernández et al. 2020; Park and Jang 2014). The effect of lodging and hotels is evident for DC as reported by prior research in terms of quality and service (Assaf et al. 2015; Chin et al. 2017; Manrai et al. 2020). Especially, international hotel chains' presence lends a sense of reliability and global quality standards to a destination (Assaf et al. 2015). Assaf and Tsionas (2015) and later Manrai et al. (2020) emphasize that quality accommodations and service excellence enhance DC, with international hotel chains playing a significant role due to their high standards and global brand presence. This study employs WTC to delve into the intricate relationships between key performance indicators in hotel RM and their impacts on DC. WTC offers a fruitful analysis framework to assess the complexity of the DC which incorporates dynamic and non-linear interactions which may create significant changes in a destination's competitiveness (Altınay and Kozak 2021).

Performance data with various metrics pave the way for an analytical approach to incorporate multiple factors with their (non)-linear relationships. Specifically, revenue practices in hotels are critical factors for destinations (Kuokkanen and Bouchon 2021). Studies by Madanoglu and Ozdemir (2016) and Chattopadhyay and Mitra (2019) utilize techniques to delve into the time–frequency relationships between performance metrics like ADR and RevPAR, offering deeper insights into the dynamics of DC. Performance analysis, productivity, and pricing are among the core indicators of hotel competitiveness used for strategic decisions (Tsai et al. 2009). Performance analysis based on ADR, RevPAR, and other financial metrics as core elements of hotel RM continues to be a current topic in the RM field, mainly in relation to the pricing practices of hotels as per its role for successful business analysis (Binesh et al. 2021; Denizci Guillet 2020). Moreover, the effects of crises like COVID-19 can also be monitored on those revenue metrics (Ozdemir et al. 2021). For the evaluation of the competitiveness of the urban markets, it is important to use key industry metrics such as supply and demand trends, ADR, OCC, and RevPAR, as emphasized by Madanoglu and Ozdemir (2016) and Chattopadhyay and Mitra (2019). The variety and interrelationships of these metrics offer fruitful grounds for WTC for a refined competitive analysis and perspective of performance evaluation.

Each hypothesis in the current study is designed to explore the lead-lag dynamics between supply-related metrics and their outcomes in terms of demand and revenue-related efficiency. As this study aims to develop a more focused approach using WTC for DC based on the hotel RM data in the major European cities, it offers a deeper understanding of how hotel RM performances influence the broader context of DC by validating these hypotheses through empirical analysis. The following hypotheses have been developed in this respect.

H_1: In the selected destinations, supply metrics lead the demand dynamics in the hotel industry.

This hypothesis builds on the foundational principle that supply dynamics, such as room availability and capacity adjustments, have a direct and anticipatory impact on demand. Supply adjustments can significantly influence booking behaviors and demand forecasts, particularly in tourist-centric urban environments (Madanoglu and Ozdemir 2016). Recent empirical research by Niavis and Tsiotas (2019) and Gómez-Vega and Picazo-Tadeo (2019) provides a nuanced understanding of how balancing and integrating supply (infrastructure and services) and demand (tourist expectations and behaviors) factors are crucial for sustaining DC. In addition, the effect on demand is more evident in crises such as COVID-19 (Dogru et al. 2023).

H_2: In the selected destinations, supply metrics lead revenue generation in the hotel industry.

Given that RM is critically dependent on the effective alignment of supply with market demand, this hypothesis examines whether proactive supply management can predict and drive revenue outcomes. Studies such as those by Chattopadhyay and Mitra (2019) highlight the strategic importance of supply in optimizing revenue, suggesting a direct relationship where supply changes precede revenue fluctuations.

H$_3$: In the selected destinations, supply metrics precede and influence RevPAR in the hotel industry.

This hypothesis tests the direct influence of supply on RevPAR, a critical metric that combines aspects of pricing and occupancy. The idea is that supply not only affects occupancy through demand but also impacts RevPAR directly through its influence on room rates and available inventory (Singh and Corsun 2023). In addition, hotel businesses are key actors in deciding on prices as per their orientation and expertise to assess the demand for a destination (Kuokkanen and Bouchon 2021).

H$_4$: In the selected destinations, ADR leads and determines occupancy rates in the hotel industry.

Pricing strategies are pivotal in the hotel industry. Hotel prices have a key role for DC in terms of tourist choice and hotel revenues (Xie and Tveterås 2020). This hypothesis proposes that ADR, a key indicator of pricing strategy, sets the pace for occupancy levels, asserting that higher ADRs, indicative of perceived value and quality, lead to higher occupancy. This relationship is pivotal in urban tourism markets, where pricing flexibility can significantly influence guest booking decisions (Dwyer and Kim 2003).

4 Methodology

The aim of this study addresses at developing a focused approach for DC based on the hotel RM data in the case of European city destinations by assessing the competitiveness of major European cities using WTC. Therefore, revenue-related performance of hotels in a destination can be scrutinized to the DC assessment. The study incorporates longitudinal RM data of upscale and higher-level hotels between the years 2013–2022. The study focuses on the fundamental KPIs of hotel RM and utilizes WTC to analyze the competitiveness of major European cities (Istanbul, London, Madrid, Paris, and Rome), representing the top five tourism countries.

4.1 Wavelet coherence analysis

Wavelet coherence analysis (WTC) is a powerful tool for analyzing non-stationary frequency data and is superior to other methods such as Fourier analysis, thanks to the examination of the time-varying dynamics of data at different frequency scales. WTC works by decomposing a signal into a set of wavelet coefficients, representing the signal's energy at different time–frequency scales. WTC can localize frequency decomposition, identifying the frequency components of a signal at specific points in time. Additionally, WTC is effective at handling signals with a wide range of frequencies, from very low to very high. A wavelet function is defined as follows, where ω_o is frequency and n is time:

$$\psi_0(n) = \pi^{-1/4} e^{i\omega_0 n} e^{-1/2n^2}$$

Wavelet transformations act as band-pass filters, and their application to time series allows them to be eliminated and then reconstructed. Wavelet transforms allow localization of frequency decomposition and produce information about frequency components. A wavelet is an integrable function with a zero mean that is frequency and temporally localized. The Morlet wavelet (with $\omega_o = 6$) is an effective choice for component extraction when utilizing WTC. It provides a good balance between temporal and frequency localization (Grinsted et al. 2004). The Morlet wavelet is a popular choice for WTC especially for time–frequency analysis (Zaki 2022).

WTC is a versatile tool, and among its various implementations, the continuous wavelet transform (CWT) stands out for its detailed time–frequency decomposition. CWT is a type of WTC that provides information about the frequency content of a signal at all points in time. This makes it ideal for assessing signals with variable frequency content over time, such as speech or music. CWT achieves this by breaking the signal down into wavelet components of varying sizes and locations. Each component is a wavelet function that has been scaled and shifted to cover a specific section of the time–frequency plane. The convergence of CWT is defined as follows, where * denotes complex conjugate:

$$W_x(\tau, s) = \frac{1}{\sqrt{s}} \sum_{t=1}^{N} x_t \psi^* \left(\frac{t-\tau}{s} \right)$$

Torrence and Compo (1998) designate the cross-wavelet transform (XWT) of two time series, x_n and y_n, as $W^{XY}(u,s) = W^X(u,s)W^{Y}*(u,s)$. The position index is denoted by u, while the scale is denoted by s. The cross-wavelet power, reflecting the time series' local covariance at each scale, is denoted as $|Wxy(u,s)|$. Wavelet coherence is used to find the co-move areas of two time series in the time–frequency domain. The squared wavelet coherence coefficient is calculated as follows by Torrence and Webster (1999):

$$R_s^2(u, s) = \frac{|S(s^{-1}W_{xy}(u, s)|^2}{S(s^{-1}\left|W_x(u, s)\right|^2)S(s^{-1}|W_y(u, s)|^2)}$$

S is the smoothing operator. The coefficient values will be in the range of 0 and 1. If the value gets close to 1 (zero), it provides proof of strong (weak) correlation. The temporal lag between two time series can be calculated using the wavelet coherence phase. The phase difference is determined as:

$$\psi_{xy}(\mathrm{u},\ \mathrm{s}) = tan^{-1}\left(\frac{I\left\{S\left(\left(s^{-1}W_{xy}(u, s)\right)\right)\right\}}{R\left\{S\left(\left(s^{-1}W_{xy}(u, s)\right)\right)\right\}} \right)\psi_{xy} \in [-\pi, \pi]$$

where I and R are the imaginary and real sections of the power spectrum, respectively. If the phase difference between the two time series is zero, they are said to be moving in the same direction. If the phase difference is positive, the first time series is ahead of the second. When the phase difference is negative, the second time series is ahead of the first. This knowledge can be utilized to forecast how the data will evolve in the future and to comprehend the relationship between two time series.

Using WTC, this formula examines two time series and determines the phase difference between them, which reveals the timing and direction of their interaction. On coherence plots, the phase difference is graphically represented by arrows, indicating the direction and intensity of the relationship between the time series. A zero-phase difference suggests that both time series are moving in the same direction. If the time series has a positive (or negative) correlation, the arrows point to the right (or left), while arrows pointing up indicate that the first time series is ahead of the second, and arrows pointing down suggest the second time series is ahead of the first (Barunik and Vacha 2013). Additionally, the colors on the plot, ranging from blue to dark red, represent the strength of the coherence, with blue indicating low coherence (weak or no correlation) and dark red indicating high coherence (strong correlation) at specific frequencies and times.

The CWT exhibits boundary artifacts because the wavelet is not entirely localized in time. Due to discontinuity, the wavelet power reduces to e^{-2} at the edges. To avoid this problem, the time series should be padded with enough zeroes. As a result, introducing a cone of influence (COI) is more efficient. By using the COI, researchers may visually identify the areas of the time–frequency plane where WTC should be used with caution. This allows for a more exact assessment of the time series' localized properties and dynamics while accounting for any distortions produced by its finite length and boundary effects (Grinsted et al. 2004).

The WTC method has been effectively employed in recent studies to analyze complex economic and financial interactions during the COVID-19 pandemic. Ullah et al. (2023a) used this method to investigate the impact of COVID-19 on China's business and economic conditions, revealing the importance of quantile asymmetries. By decomposing time series data into different frequency components, WTC allowed for the identification of time-variant relationships, highlighting how different quantiles of economic variables responded differently to the pandemic over time (Ullah et al. 2023a). Similarly, another study by Ullah et al. (2023b) applied WTC to examine the effects of COVID-19 and economic policy uncertainty on China's stock market returns. This approach captured the complex interactions between stock market returns and uncertainty at different time scales, showing varying degrees of co-movement and causality during the pandemic (Ullah et al. 2023b). Additionally, Syed et al. (2024) utilized WTC and spectral causality to assess the impact of COVID-19 and lockdown stringency on foreign institutional investment in India. Their analysis pinpointed periods of high and low coherence, demonstrating the dynamic nature of investment flows and lockdown measures across different time and frequency bands (Syed et al. 2024). These studies illustrate the versatility and robustness of WTC in capturing the intricate, time-varying relationships inherent in economic and financial data, particularly during unprecedented events like the COVID-19 pandemic.

WTC is also a recent method applied in research in the tourism field. Zaki (2022) assessed the RM practices in the pandemic period. That study reports high correlations of COVID-19 and RM practices in the overall business cycle. Another study with a focus on pandemic effects on hotel occupancies reveals a convergence pattern in the hotel occupancy rates at the first wave of the pandemic (Polemis et al. 2023). In a wider spectrum, WTC can be utilized with other techniques to generate insights for economic development in destinations (Cao et al. 2016). This method is also fruitful to reveal various interrelationships of tourism flows with macroenvironment factors such as economic growth (Kumar et al. 2019), geopolitical risk (Balli et al. 2019), foreign aids and GDP (Das et al. 2023), and political and economic matters (Aloui et al. 2021).

The capability of the WTC to reveal (non)-linear time–frequency relationships pave the way to benefit from hotel RM data to assess DC. Figure 2 illustrates the study framework.

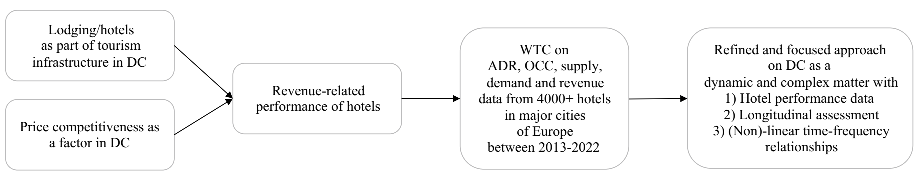


Fig. 2 DC assessment by hotel performance. *Source*: Authors' own production

As seen in Fig. 2, the current study proposes a novel perspective on DC assessment as a different orientation from prior research with a focus on hotel revenue-related performance using longitudinal data to reveal (non)-linear relationships leading to an understanding of the competitive positions of the major European city destinations.

4.2 Analysis framework and process

In accordance with the study aim, the research question has been formulated to understand if hotel performance data, specifically measured by revenue-related metrics, are effective to assess the competitiveness of destinations in the case of major European tourism cities. Given the power of WTC to analyze (non)-linear relationships between variables, this competitive assessment was conducted through four different pairs of hotel RM KPIs: (1) Supply and demand, (2) supply and revenue, (3) supply and RevPAR, (4) ADR and OCC. The trended daily data of those KPIs for the 10-year period (2013–2022) belonging to the selected tourism cities were obtained from Smith Travel Research (STR) and taken into WTC analysis. The methodology, based on WTC, is justified through its ability to detect, and analyze non-linear, time–frequency relationships over a decade. This approach allows for a nuanced understanding of the dynamics affecting DC, underscoring the method's appropriateness for the study's objectives.

The trended daily data of fundamental hotel RM metrics for the 10-year period (2013–2022) of the five cities were obtained from STR to conduct competitive analysis using WTC. STR offers an extensive dataset of hotels that can be analyzed by sophisticated methods for comparison and performance purposes (Al Shehhi and Karathanasopoulos 2020; Litvin and Fetter 2006; Park et al. 2022; Sharma et al. 2022). The first stage was to scan the extensive data table to detect the level of missing values for a reliable WTC. Upscale, upper upscale, and luxury scale properties were taken into the analysis given their complete data of the RM metrics. Al Shehhi and Karathanasopoulos (2020) also included luxury and upscale properties, most probably for the same reason. This fact confirms that hotels in a destination show a heterogeneous pattern of RM utilization, and RM is mainly an issue for large-scale upper segment hotels (Ivanov et al. 2021). In addition, RM is an approach particularly applied in large urban hotels with upper categories and chain affiliations (Abad et al. 2019; Ivanov et al. 2021). Table 1 shows the attributes of the cities with the properties included in the study.

As seen in Table 1, the study includes a dataset of more than 4000 hotels. London is the leading city with the highest accommodation capacity, with a substantial difference from other cities. In addition, the intensity of upscale and upper segments is higher in London, Paris, and Rome. However, the response rate is much higher in Madrid and Istanbul, which can be explained by the share of international hotel groups. Upon the compilation of the data for analysis, the competitive analysis was carried out using specific KPI pairs of RM, which were taken into the WTC process to reveal coherencies of those metrics: (1) Supply and demand, (2) supply and revenue, (3) supply and RevPAR, (4) ADR and OCC. The findings were obtained by using Grinsted et al. (2004) Matlab codes, and CWT was utilized to perform WTC on the dataset.

Table 1 Five city destinations STR profile. *Source*: STR trended data obtained upon request for this research

City	Total number of properties	Number of upscale and higher scale properties	Share of studied properties (%)	Number of response (as of the end of the year 2022)	Response rate* (%)
London	2537	1720	68	513	30
Paris	1560	1162	74	303	26
Madrid	708	384	54	204	53
Istanbul	667	316	47	164	52
Rome	632	458	72	119	26

*Response rate indicates the rate of the properties which share data with STR

5 Data analysis

In our descriptive analysis spanning from January 2013 to December 2022, we examined key hospitality metrics—Average Daily Rate (ADR), Demand, Occupancy (OCC), Revenue Per Available Room (RevPAR), and Supply—across five major urban markets: Paris, London, Madrid, Rome, and Istanbul. This multifaceted investigation provides significant insights into the dynamics and interdependencies that shape those cities' tourism and hospitality landscapes (Fig. 3 and Table 2).

Findings in Fig. 3 and Table 2 disclose insightful outlook of the cities in the research. Paris exhibited the highest ADR, averaging 241.46, with significant variability likely driven by seasonal and event-based factors, contrasting with Istanbul's more stable and lower ADR. This highlights diverse pricing strategies influenced by local market conditions. A strong correlation in ADR movements between Paris and London (0.72) suggests similar responses to macroeconomic changes, which was particularly evident in their sharp recovery post-2020 following the initial dips caused by the COVID-19 pandemic. Demand analysis showed Paris and London with synchronized fluctuations and the highest correlations (0.92), reflecting their mutual susceptibility to similar economic and tourist activities. The dramatic drop in demand across all cities at the onset of the pandemic, followed by a vigorous recovery, underscores the profound global impacts on local tourism markets.

Occupancy rates in London and Paris were the highest yet displayed substantial fluctuations, with pronounced declines during the pandemic. The recovery phase highlighted the resilience of these markets, with occupancy rates bouncing back robustly post-2020, further evidenced by strong occupancy correlations between these cities. RevPAR in Paris was marked by significant volatility, indicating high sensitivity to external events. The interconnected RevPAR dynamics between cities, especially between Paris and London (0.81) and Paris and Rome (0.83), indicate a collective market behavior that underscores the importance of strategic revenue management in these regions. Supply data revealed high variability in Paris and London, with sharp declines in 2020 due to the pandemic's impact. The subsequent recovery illustrated the dynamic nature of supply adjustments in response to market conditions, with particularly strong rebounds in Paris and London. This integrated analysis not only highlights the unique characteristics and interlinkages among these key markets but also illustrates the broader economic and global factors influencing the hospitality industry. Understanding these patterns is crucial for stakeholders engaged in strategic planning, investment decisions, and operational adjustments within the competitive landscape of global urban tourism.

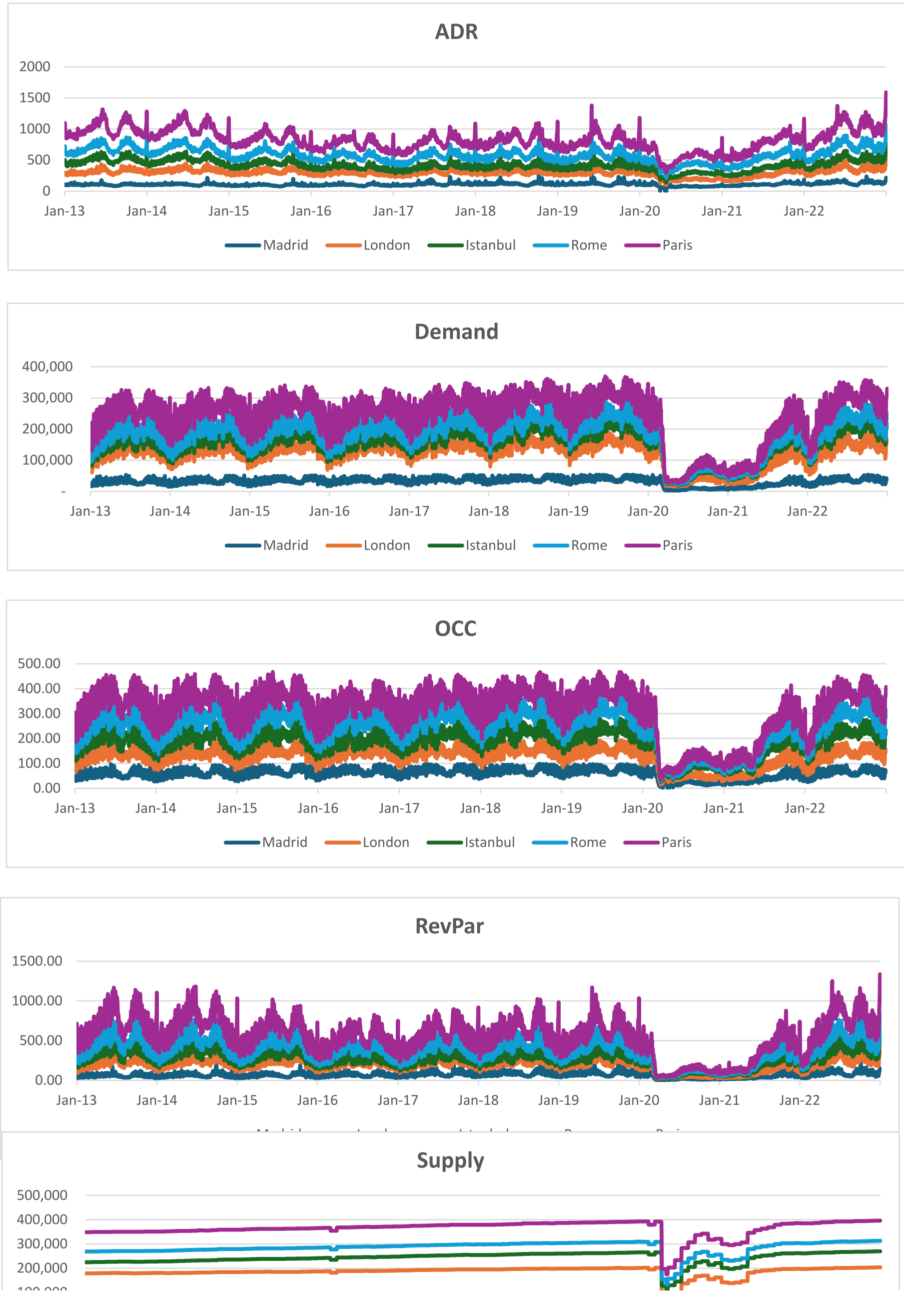
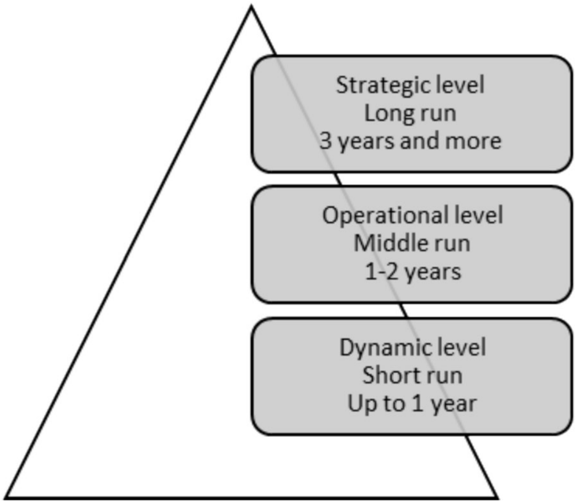


Fig. 3 Daily values of ADR, Demand, OCC, RevPAR, Supply

Table 2 Correlation matrix of five cities' ADR, Demand, OCC, RevPAR, Supply daily values between January 2013 and December 2022

Corr. Matrix	Madrid	London	Istanbul	Rome	Paris	Corr. Matrix	Madrid	London	Istanbul	Rome	Paris
ADR						*Demand*					
Madrid	1	0.47	0.13	0.51	0.50	Madrid	1	0.89	0.60	0.85	0.86
London	0.47	1	0.55	0.58	0.72	London	0.89	1	0.65	0.89	0.92
Istanbul	0.13	0.55	1	0.61	0.72	Istanbul	0.60	0.65	1	0.57	0.62
Rome	0.51	0.58	0.61	1	0.77	Rome	0.85	0.89	0.57	1	0.90
Paris	0.50	0.72	0.72	0.77	1	Paris	0.86	0.92	0.62	0.90	1
OCC						*REVPAR*					
Madrid	1	0.85	0.60	0.84	0.84	Madrid	1	0.67	0.32	0.69	0.62
London	0.85	1	0.67	0.88	0.92	London	0.67	1	0.61	0.79	0.81
Istanbul	0.60	0.67	1	0.66	0.70	Istanbul	0.32	0.61	1	0.62	0.72
Rome	0.84	0.88	0.66	1	0.89	Rome	0.69	0.79	0.62	1	0.83
Paris	0.84	0.92	0.70	0.89	1	Paris	0.62	0.81	0.72	0.83	1
Supply											
Madrid	1	0.87	0.32	0.91	0.95						
London	0.87	1	0.62	0.81	0.91						
Istanbul	0.32	0.62	1	0.10	0.35						
Rome	0.91	0.81	0.10	1	0.95						
Paris	0.95	0.91	0.35	0.95	1						

Fig. 4 Time ranges for RM. *Source*: Authors' own production



6 Results

The results are articulated in a manner accessible to non-experts, with coherent visualization and explanations that elucidate the complex relationships between hotel performance metrics and DC without requiring advanced statistical knowledge. The interpretation of findings from WTC requires knowledge of elements used in the diagrams, which reflect the coherencies of KPIs. The coherence diagrams are shown for each pair in a bivariate outline (Zaki 2022). The left vertical axis refers to the period scale (short, medium, long run), while the right vertical axis denotes the frequency scale. Blue areas reflect weak relationships, whereas red and dark orange spots reflect strong relationships. Therefore, the plots show the connected relationships from 500 to 3500 days, covering a 10-year period. The 'X-axis' indicates the KPI values from January 01, 2013 to December 31, 2022. The bold black outline describes significant areas at the 0.95 level.

The first primary finding of the analysis is the determination of time ranges to be used for RM models and RM performance evaluations, leading to business analysis and strategy formulation in the hotels and destinations (Fig. 4).

Time-based levels of actions are vital for RM models and RM performance evaluations so that hotel professionals manage their efforts of business analysis and strategic formulation. As seen in Fig. 4 and all the diagrams in the following sections, the time ranges appear as up to one year for a short run with action-based dynamic RM level, which includes the implementation of transactional procedures to increase the profitability of hotels. The operational level with one to two years for middle run addresses the necessity to consider seasonality factors, special events, and other more certain happenings that may affect dynamic level actions throughout the current year. Finally, the long run with strategic orientation refers to fundamental RM policies of hotels that determine the direction of how operational level RM actions will be managed. As seen in Figs. 6 and 7, the strategic level is limited to only 3 years for hotels where professionals need.

The second critical finding is the clear effect of the pandemic with highly positive correlations between 2000 and 3000 scales, which refer to the pandemic period (the end of 2019 to the end of 2021). COVID-19 pandemic effects were more severe in the cities dominated by foreign tourism (Widz et al. 2022).

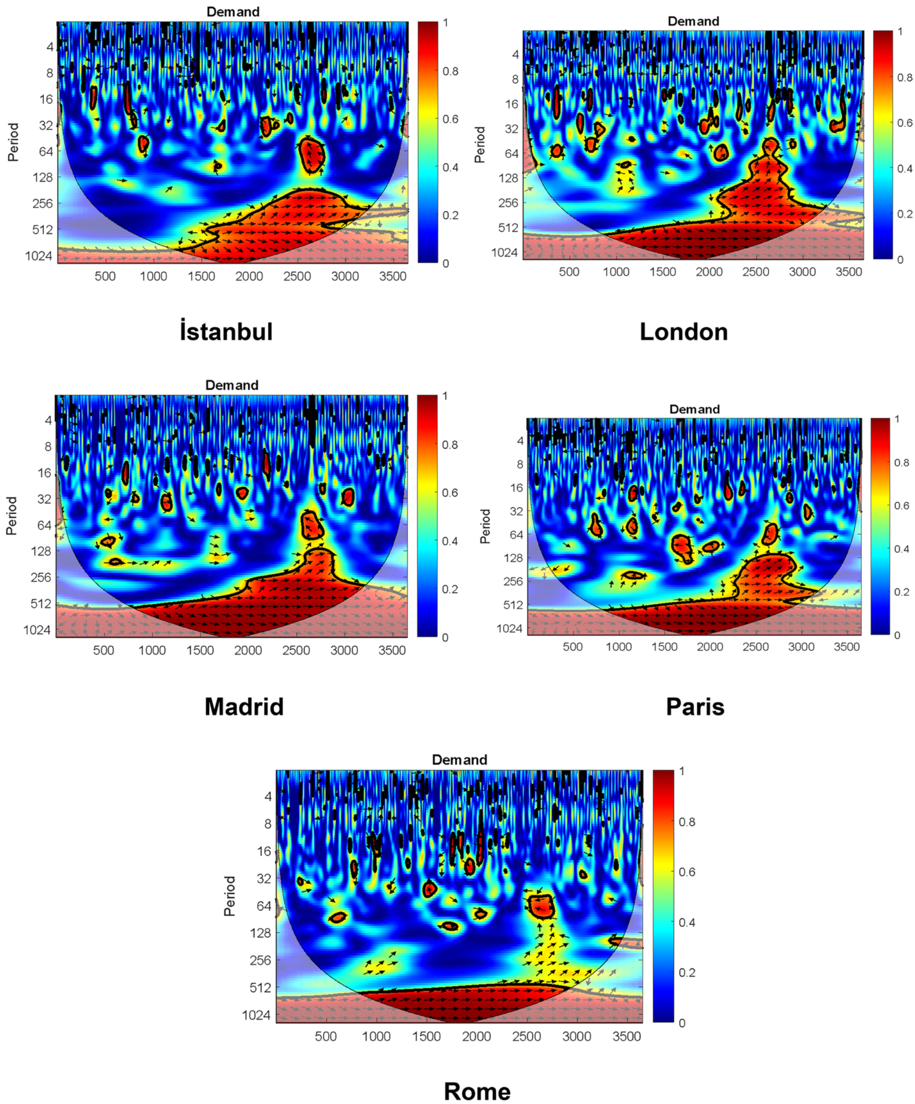


Fig. 5 Supply and demand coherence diagrams for city destinations. *In the diagrams, blue indicates low coherence (weak or no correlation) and dark red indicates high coherence (strong correlation). The points refer to the following time periods: 500-May 2014, 1000-Sept. 2015, 1500-Feb.2017, 2000-June 2018, 2500-Nov. 2019, 3000-March 2021, 3500-August 2022. **The figure shows supply and demand coherence diagrams for city destinations (dark red areas between 2500 and 3000 show high correlations and refer to the period between November 2019 and March 2021). (Color figure online)

6.1 Supply–demand coherence

Figure 5 shows the supply and demand coherence diagram. As seen in the diagram, a high correlation is observed in all the cities in the long term on between 512 and 1024 scale. The period of this very high correlation is critical to note, as the scale refers to the period between November 2019 and March 2021 for supply and demand relationships. Since the arrows shows to right in every scale supply and demand has positive correlation and at 256 scale supply leads the demand. This period shows the rapid influence of COVID-19 in the hotel industry a few months before the travel restrictions and official pandemic announcements in the countries. Hotels started to feel the negative effects of the pandemic with cancellations, especially of group businesses, which are crucial operations for shoulder seasons.

Although all cities show highly positive coherence in the supply–demand relationship between late 2019 and early 2021, the differing situation of Rome, with lower correlation, needs further explanation. Between late 2019 and 2021, the European hospitality industry was characterized by volatile shifts in supply and demand. Cities like Istanbul, Paris, London, and Madrid had their individual journeys, but Rome's path was particularly notable, differing distinctly from its peers. By the end of February 2020, Italy had transitioned from a few isolated cases to the European hotspot for the COVID-19 outbreak. By March, Italy reported over 100,000 cases (La Maestra et al. 2020). To tackle the rapidly growing health emergency, the Italian government imposed a strict nationwide lockdown by March 9, 2020 (Silverio et al. 2020). The severity and duration of Rome's restrictions outlasted those in many of its European neighbors. Preliminary figures from that era indicate nearly a 90 percent drop in primary tourist activities like hotel stays, flight entries, and even local journeys (Folinas and Metaxas 2020). In contrast to cities like London or Paris with strong financial sectors to offset the damage, Rome's dependency on tourism made it especially susceptible. As the pandemic dragged on, numerous businesses associated directly or indirectly with tourism confronted severe challenges. The media also played a pivotal role in molding global perceptions during this phase (Chemli et al. 2022).

6.2 Supply-revenue and supply-RevPAR coherence

Figure 6 shows the supply and revenue coherence diagram. Although the diagrams seem similar in all the cities, there are differentiated spots that need clarification. In addition, the situation of Rome, with low correlations between supply and revenue, shows a similar pattern as in the case of the supply–demand relationship, given the reasons explained in the previous section. The situation of Rome in the diagram affirms the high adverse effects of the pandemic in the country and city, which created severe challenges to manage, also for hotel businesses.

One remarkable finding in Fig. 6 is the higher RM competence in the hotels in London, as per the distributed correlations in all the periods ranging from 64 to 1024 scales (short and long terms), and a more seamless high positive correlation in the pandemic period. As seen in Fig. 6, all the destinations except for Istanbul show a similar pattern of high coherence in the long run of the 1024 scale. The Istanbul market also shows a quite different pattern in the supply-revenue coherence as a lower correlation in the long run but an increase as a significant positive coherence in the 1024 scale during the years 2018–2021 where the supply leads the revenue. Other than those dates, these two variables have low coherence. This shows a higher use of RM competitive data and more concentration in the RM practices in the relevant period. One reason for this fact is the increase in the number of

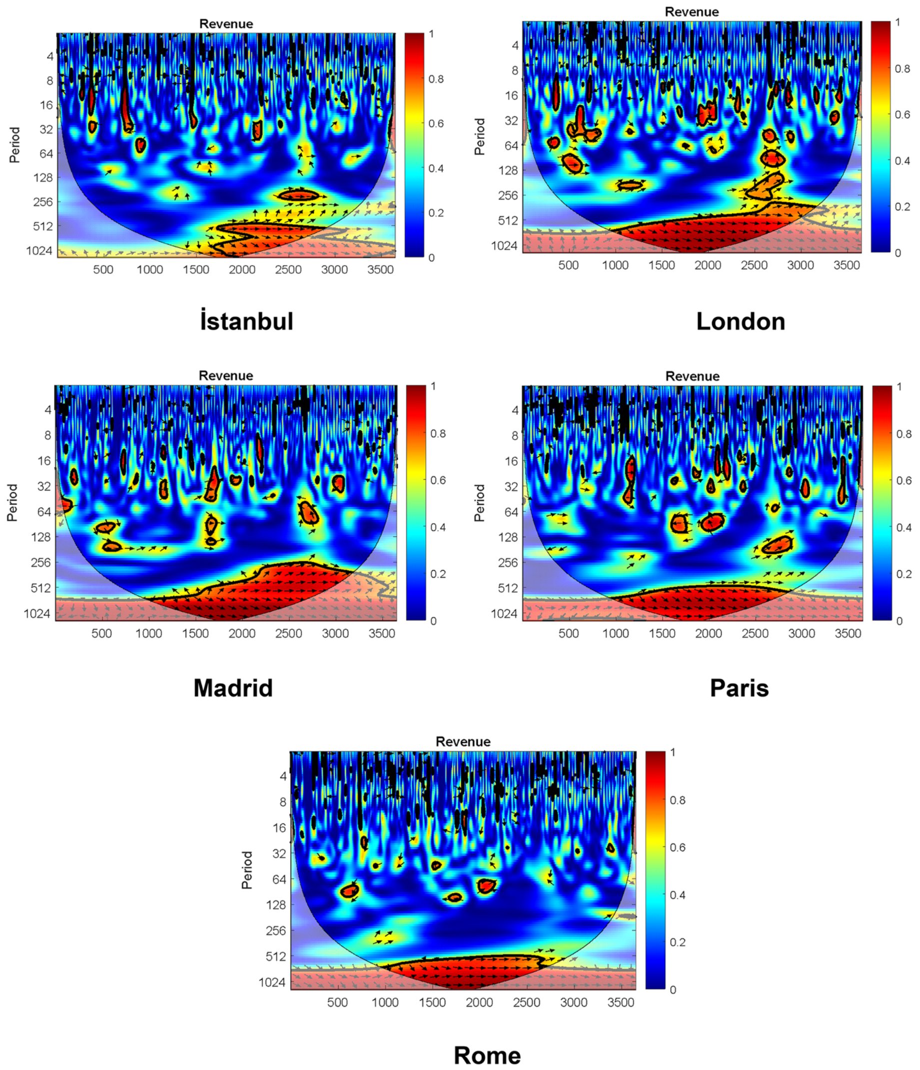


Fig. 6 Supply and revenue coherence diagrams for city destinations. *In the diagrams, blue indicates low coherence (weak or no correlation) and dark red indicates high coherence (strong correlation). The points refer to the following time periods: 500-May 2014, 1000-Sept. 2015, 1500-Feb.2017, 2000-June 2018, 2500-Nov. 2019, 3000-March 2021, 3500-August 2022. **The figure shows supply and revenue coherence diagrams for city destinations (in scale 1024, all the destinations except for Istanbul show high correlations and dark red areas between 2000 and 3000 show high coherence and refer to the period between June 2018 to March 2021). (Color figure online)

international chains in the city with higher expertise in the field. This can also be explained by the higher use of RM competence during the pandemic period under the high uncertainty of external and sectoral conditions. As a supportive finding for supply-revenue coherence, Fig. 7 shows the supply and RevPAR coherence diagram.

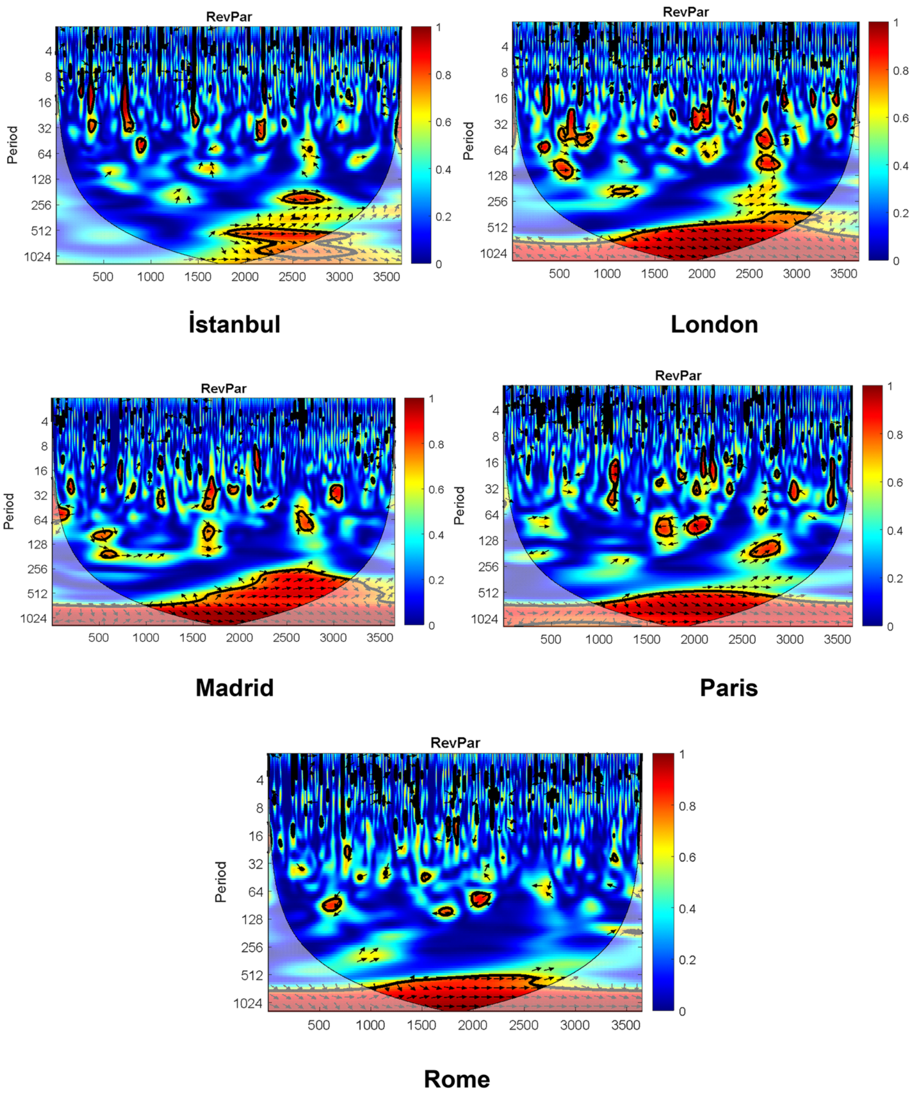


Fig. 7 Supply and RevPAR coherence diagrams for city destinations. *In the diagrams, blue indicates low coherence (weak or no correlation) and dark red indicates high coherence (strong correlation). The points refer to the following time periods: 500-May 2014, 1000-Sept. 2015, 1500-Feb.2017, 2000-June 2018, 2500-Nov. 2019, 3000-March 2021, 3500-August 2022. **The figure shows supply and RevPAR coherence diagrams for city destinations (in scale 1024, all the destinations except for Istanbul show high correlations and dark red areas between 2500 and 3000 show high coherence and refer to the period between November 2019 to March 2021). (Color figure online)

6.3 ADR–OCC coherence

Figure 8 shows the supply and revenue coherence diagram, which confirms that ADR leads OCC in all the cities, with a balanced relationship between ADR and OCC in those cities.

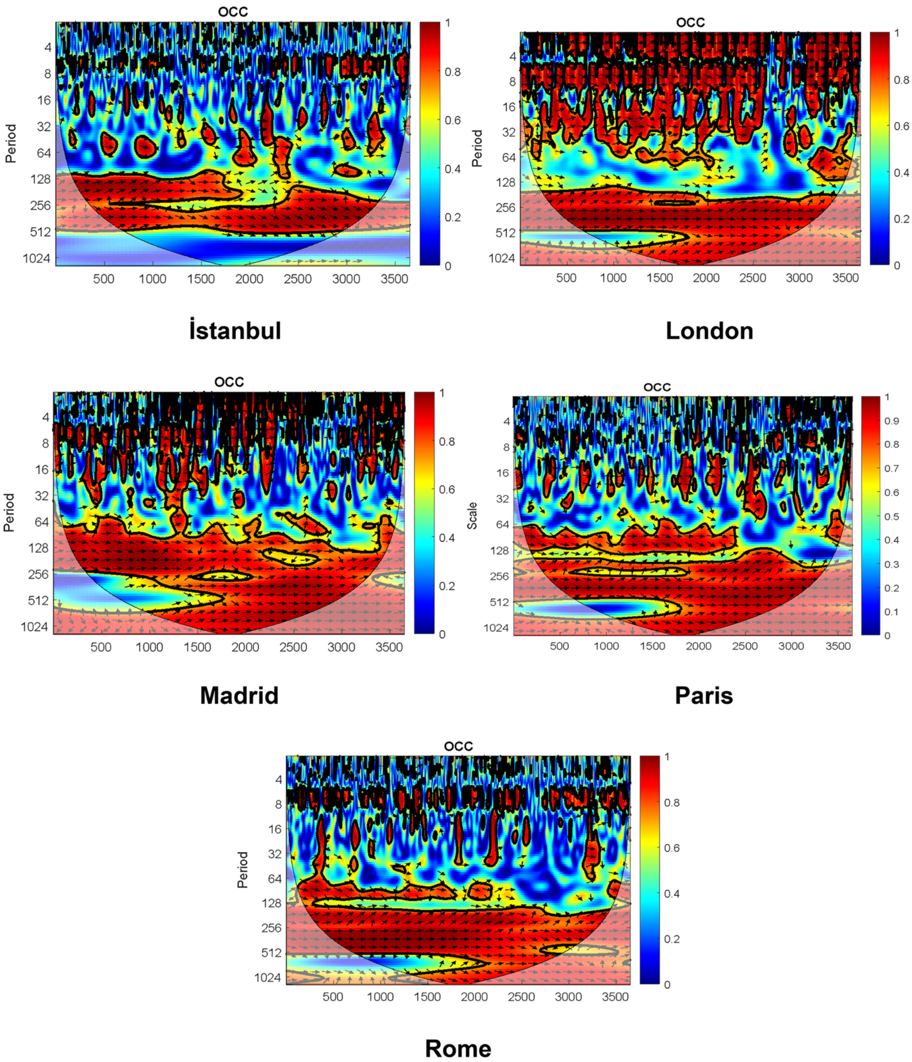


Fig. 8 ADR and OCC coherence diagrams for city destinations. *In the diagrams, blue indicates low coherence (weak or no correlation) and dark red indicates high coherence (strong correlation). The points refer to the following time periods: 500-May 2014, 1000-Sept. 2015, 1500-Feb.2017, 2000-June 2018, 2500-Nov. 2019, 3000-March 2021, 3500-August 2022. **The figure shows ADR and OCC coherence diagrams for city destinations (dark red areas refer highly correlated periods between January 2013 to December 2022). (Color figure online)

A similar situation also appeared in the RevPAR-OCC analysis, which was not included in the paper as per undifferentiated findings from the ADR-OCC coherence analysis.

Diagrams in Fig. 8 show similar patterns but with different levels of ADR-OCC coherence in the cities. London, with the highest correlations, appears as the city with a more advanced level of RM competence in hotels. On the other hand, Istanbul, with lower ADR-OCC correlations than other cities in general but higher correlations in the 256–512 days period, which refers to middle-run operational-level RM practices (Fig. 4). This means that

RM professionals in Istanbul focus more on operational actions depending on more static conditions of the business environment, such as seasonality and market segmentation in certain months. However, those professionals need to improve their competence for RM strategy formulation and dynamic decision-making actions to reap higher benefits of their RM efforts, which also need to penetrate the industry, including independent hotels.

7 Discussion

Given the power of WTC to reveal (non)-linear relationships, the study findings present some destination-specific situations that may affect the competitiveness of the cities. First of all, the coherences of all the tested relationships (supply–demand, supply–revenue, supply–RevPAR, ADR-OCC) demonstrate the adverse effects of the pandemic in all the destinations before the official announcements of cases and travel restrictions. This critical finding reflects the sensitivity of the tourism and hotel industry to crises, which may have severe effects on DC, as COVID-19 pandemic effects were significant in the cities dominated by foreign tourism (Widz et al. 2022).

However, the coherence diagrams demonstrate higher challenges for Rome given pandemic-related causes (number of cases) and dependence on the destination's tourism-related economic environment. Therefore, as a DC-related finding, Rome appears to be a more fragile city destination among the others. This finding confirms the effect of external and situational factors on DC, as stated in the prior research (Dwyer and Kim 2003). In addition, high correlations of those coherences during the pandemic also prove the goal of destinations to strive for a higher market share to sustain their DC (Cronjé and du Plessis 2020; Tsai et al. 2009) by focusing on market share and revenue generation index metrics of hotel RM (Guillet and Chu 2021).

On the other hand, London is the city with a higher competitive advantage based on a healthier hotel RM environment and higher RM competence, as seen in the supply-revenue and ADR-OCC coherences based on a balanced distribution of correlations in all the periods (short and long term). The success of the city can be explained by the destination-specific factors such as commercial and business potential and international access (Enright and Newton 2004). As also seen in Table 1, the number of upper-class hotels is also very high in that city, which has a positive effect on the DC (Assaf et al. 2015).

Finally, based on the findings, the competitive situation of Istanbul also needs clarification. As seen in the supply-revenue and supply-RevPAR coherences with higher correlations in the short run during the pandemic in that city; however, the same pattern of high correlation is not a long-term situation. Therefore, findings reveal that the DC of Istanbul city may be improved by higher RM-related knowledge and skills in the hotels and destination. The pandemic revealed the critical role and competence of RM professionals and practices supported by enhanced digitalization to manage the crisis by reducing its negative effects (Talón-Ballestero et al. 2023). Qualified RM professionals are one major determinant of successful RM implementation in hotels (Abad et al. 2019) which may improve hotel performances with a positive effect on DC (Dwyer and Kim 2003; Enright and Newton 2004; Fernández et al. 2020; Tsai et al. 2009). Notwithstanding, the higher use of RM competitive data and more concentration in the RM practices between 2018 and 2021 can also be explained by the increase in the number of international chains in Istanbul with higher RM expertise.

The overall findings of the study based on hotel RM metrics offer WTC as a new analysis framework to assess DC which still needs new methods of measurement (Fernández et al. 2020). Despite vast research on DC, there still exists a need for other aspects than the supply side to enhance the understanding of this prominent topic in the tourism field (Cronjé and du Plessis 2020). As the study findings demonstrate relationships between supply and other metrics such as demand, revenue, and RevPAR, the application of WTC on hotel RM data produces some valuable insight into DC in relation to demand-related factors. In addition, using hotel RM-related metrics appears to be effective to assess the role of DC on the performance of hotels in that place (Tsai et al. 2009). As WTC used in this study focuses on (non)-linear relationships between KPIs in the most visited cities of Europe, the study findings underline the application of effective RM strategies to reap the benefits of the higher competitive advantage.

On the other hand, given the role of the lodging facilities as an influential factor in DC (Enright and Newton 2004; Fernández et al. 2020), the study findings from WTC enhance the current understanding of competitiveness with the use of recent metrics of the sector. Study findings with relatively higher correlations of coherences also confirm the results of Spain, France, and the United Kingdom, which are among the top five competitive tourism countries globally (Gómez-Vega and Picazo-Tadeo 2019). The competitive situation of Istanbul with the need for developing RM-related strategic orientation and expertise may give a clue to improve the competitive ranking of Türkiye as a tourism destination.

Finally, the availability of a complete RM dataset of upper-class hotels made it possible to conduct this research as a novel method of applying WTC to assess DC of cities. The use of data from upper-class hotels is effective to conduct competitive analysis, as also applied in prior research (Al Shehhi and Karathanasopoulos 2020). This study also revealed the fact that RM in hotels is mainly a matter for large, upper-class, and chain-affiliated hotels in a destination (Abad et al. 2019; Ivanov et al. 2021). Although the presence of such competent international hotels is a driving force for DC in cities (Assaf et al. 2015), the dissemination of RM practices to other hotel classes offers promising potential to improve DC, as per the importance of hotel performances as an influential factor.

8 Conclusion

The major theoretical contribution of the current study is the novel and focused perspective based on hotels' revenue-related performance which was analyzed by WTC as hotels constitute a major determinant of DC as a part of the tourism infrastructure in a destination. The study is the first one to utilize WTC on hotel RM metrics and proposes an extensive assessment of DC based on a large (more than 4000 hotels in five cities) and longitudinal dataset between the years 2013–2022. The novel model proposed in the current study permits a sophisticated exploration of (non)-linear time–frequency relationships between RM metrics in hotels, presenting a deeper and more nuanced understanding than traditional correlation analyses. These metrics provide a holistic insight into each city's tourism performance, market behavior, and potential allure, offering an elaborate assessment of their individual and comparative market outcomes. Besides presenting a wide-ranging comparative review, this research also delves into detailed evaluations specific to each city, scrutinizing individual fluctuations in RevPAR, supply, and demand during the assessment period.

The paper presents a novel approach by applying WTC to assess DC through the lens of hotel revenue performance. The study uniquely contributes to the field by analyzing time–frequency relationships among hotel revenue variables across major European cities, revealing how these dynamics impact DC. This methodology offers a fresh perspective on evaluating DC, emphasizing the strategic role of hotel RM in urban tourism markets. WTC enables a refined understanding of the elements influencing each city's tourism sector, thereby enhancing the overall grasp of the dynamics and competitiveness present in urban tourism. By leveraging WTC, the paper advances global knowledge on DC, showcasing how the temporal dynamics of hotel revenue variables influence competitiveness. This progression illuminates the nuanced ways in which hotel industry performance metrics, such as supply, demand, and revenue, intersect to shape destination attractiveness, offering a comprehensive understanding of the factors that drive urban tourism success.

Therefore, the ultimate aim of the study is to benefit from the WTC method providing fresh insights into DC and offering actionable input for policymakers, destination marketers, and industry stakeholders with the use of a novel methodology that generates extensive outcomes for consideration. Given the critical role of external KPIs such as market share (demand) and the revenue generation index for a more accurate evaluation of RM practices in relation to competitors (Guillet and Chu 2021), the study achieves its ultimate aim to provide fresh insights into DC and offering actionable input for policymakers, destination marketers, and industry stakeholders. By amalgamating a robust set of RM KPIs with a novel analytical model, this study aspires to contribute to the body of knowledge in urban tourism and shed new light on the dynamics of urban tourism markets and their competitiveness.

The findings have implications for both academic research and industry practice, encouraging a longitudinal data-driven approach to understanding and improving DC. The study underscores the importance of integrating advanced analytical methods into tourism studies and strategic planning, potentially influencing policymaking and RM strategies. The Wavelet-based framework can provide unique insights that might influence policymaking efforts, social perceptions, and practical strategies within the tourism and hotel industry. From a political perspective, the nuanced understanding of the factors that enhance or hinder a city's competitiveness based on hotel RM practices can shape policymaking and strategic planning. Policymakers could use these insights to tailor their investment strategies, focusing resources on areas most likely to improve competitiveness and tourism attractiveness. As the study reveals that KPIs such as ADR, OCC, RevPAR, and their coherence significantly influence competitiveness among cities, policies could be oriented towards enhancing the quality and diversity of accommodations, introducing incentives for investment in the tourism sector, and seeking ways to raise qualified RM professionals with a strategic perspective.

On the social front, the study's outcomes could enhance community awareness about the economic and cultural implications of tourism in cities. Realizing the key factors contributing to the success of the city as a tourist destination could foster greater social support for initiatives promoting tourism, including hotels. Increased awareness in the RM-related competitiveness makes better and more profitable use of resources in a city. This orientation also fosters a new career path in the RM field for young generations with higher income and benefits to pursue a sustainable engagement in the hotel industry. Overall, the ultimate aim of the DC to support economic and social welfare in the local community can be attained. From a practical viewpoint, the findings could serve as a valuable resource for various stakeholders in the tourism industry, including business, marketing agencies, urban planners, and developers. For example, hotel and other accommodation providers could use these insights to formulate strategies aimed at increasing OCC and ADR, and therefore RevPAR as key factors in DC. Hotel investors could make accurate evaluations of the factors shaping the competitive environment within the city and in relation to other rival cities. Accordingly, intensive RM efforts will also lead the way to raise RM professionals with different levels of perspective and skills to increase the earnings of hotels and enhance the competitive advantage of cities.

Study findings could also be valuable to support sustainable development goals (SDG) for policy development with higher positive impact on societies. SDG #8 states the offering of decent work leading to economic growth in tourism destinations. A focus on DC with more analytical approach on RM data will generate a more profitable and productive business environment for hotels to offer better jobs and outcomes to the society. In addition, such orientation will also help the dissemination of this analytical perspective to support digital transformation of the industry. In this respect, SDG #9 is also under consideration to enhance innovative ongoing of the industry using fruitful outcomes of the data analytics. Therefore, policy development can be formulated on a more data-driven orientation to multiply positive effects of RM-based DC throughout the hotel and tourism industry. Finally, such orientation will also help to develop sustainable communities and cities as proposed by SDG #11 given the more profitable run of the industry which generate more income and opportunities to fund sustainability practices in destinations.

8.1 Limitations

WTC is an extensive framework to test lead-lag relations in which external factors, including either economic (currency and exchange rates, price indexes, tourist numbers, etc.) or non-economic (review or reputation scores, climate predictions, online demand patterns for destinations, etc.) indicators, can also be integrated to conduct a more comprehensive analysis of DC. Further studies can be designed on this extensive ground. In addition, other business performance indicators measuring profitability and costs, customer-related items (satisfaction, expenses), and other financial performance measures (return on assets or equity, etc.) can also be added to the analysis dataset. The WTC can also be extended to week-of-the-day and market segmentation data to reveal deeper insights for DC evaluation.

Another limitation of the study is the use of only STR data, which is limited to the hotels sharing data on the platform. As seen in Table 1, destinations include a high number of hotels, with a major part of independent properties excluded from the study as they do not provide data to the STR platform. Another limitation is the scope of the study, including the upscale and upper segment hotels with relatively higher RM orientation and expertise. Further studies could also produce comprehensive findings if the WTC framework was implemented on the RM data of other hotels in the lower segments (midscale, economy) to help the development of sustainable destination management policies throughout the total hotel industry in a city. Finally, a wide spectrum of city and/or resort destinations, for instance, the entire market of the European region, could be taken into several WTC analyses with RM-related KPIs to conduct a comprehensive evaluation of DC by comparing those places with several aspects in relation to their accommodation-related attributes.

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Declaration

Conflict of interest The authors declare that they have no conflict of interest.

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