UNIVERSIDADE CATÓLICA PORTUGUESA

Efficiency Analysis of Main European Cities in the Airbnb Market

Luis Miguel Leite Rosendo

Católica Porto Business School
September 2024

UNIVERSIDADE CATÓLICA PORTUGUESA

Efficiency Analysis of Main European Cities in the Airbnb Market

Final Work in Academic Context presented to Universidade Católica Portuguesa to obtain the master's degree in Management with a specialization in Business Analytics

by

Luis Miguel Leite Rosendo

under the guidance of
Dr Akram Dehnokhalaji

Católica Porto Business School
September 2024

Acknowledgments

First and foremost, I would like to sincerely thank Católica Porto Business School for giving me the priceless chance to attend Aston Business School and pursue a double degree. My academic path has been tremendously enhanced by this experience, which has given me a variety of viewpoints and abilities that have been quite helpful in finishing this dissertation. My schooling and potential profession have been greatly influenced by the assistance I have received from both universities.

My supervisor, Dr. Akram Dehnokhalaji, has my sincere gratitude for her steadfast support, ongoing direction, and inspiration during this process. Her guidance and support have been invaluable in helping me overcome the obstacles of this task, and her mentorship has been a vital component of my academic growth.

Additionally, I want to sincerely thank each one of the MSc Business Analytics course instructors. My classmates' collaborative environment helped me to grow both intellectually and emotionally, and their views and expertise gave me a strong basis upon which to expand. I have no doubt that the experience I've learnt from working in groups and actively participating in lectures will come in handy in the future.

Finally, I am profoundly grateful to my family and friends for their continuous encouragement throughout my master's program. A special thank you to my dearest parents and sister for their unconditional love and support, which has been a constant source of strength at every step of my journey.

Resumo

Este estudo avalia o desempenho das listagens do Airbnb em grandes cidades europeias de dezembro de 2023 a junho de 2024. Utilizando dados de 30 países, o modelo DEA (Análise Envoltória de Dados) calculou as pontuações de eficiência, com o Número de Listagens, Receita Média Mensal e Taxa de Ocupação como variáveis. O Índice de Malmquist foi utilizado para medir as mudanças na produtividade ao longo do tempo. Genebra, Praga e Estocolmo foram identificadas como as cidades mais eficientes, enquanto Nápoles foi a menos eficiente. Apesar de não serem as mais eficientes, Copenhaga e Edimburgo frequentemente serviram como referências importantes. A análise também revelou que a maioria das cidades experimentou um declínio na produtividade, embora Malta tenha mostrado um crescimento notável. As limitações, incluindo o curto período de tempo e os dados trimestrais, sugerem a necessidade de mais pesquisas para captar tendências de longo prazo. O estudo destaca a necessidade de estratégias adaptativas para se manter competitivo no mercado de alugueres de curto prazo em constante evolução.

Palavras-chave: Airbnb, Análise Envoltória de Dados, Benchmarking, Eficiência, Índice de Malmquist

Abstract

This study evaluates the performance of Airbnb listings in major European cities from December 2023 to June 2024. Using data from 30 countries, the DEA (Data Envelopment Analysis) model calculated efficiency scores, with Number of Listings, Monthly Average Revenue, and Occupancy Rate as variables.
The Malmquist Index was used to measure productivity changes over time. Geneva, Prague, and Stockholm were identified as the most efficient cities, while Naples was the least efficient. Despite not being the most efficient, Copenhagen and Edinburgh frequently served as key benchmarks. The analysis also revealed that most cities experienced a productivity decline, though Malta showed notable growth. Limitations, including the short timeframe and quarterly data, suggest the need for further research to capture longer-term trends. The study highlights the need for adaptive strategies to remain competitive in the evolving short-term rental market.

Keywords: Airbnb, Data Envelopment Analysis, Benchmarking, Efficiency, Malmquist Index

Index

Number of words: 9123

List of Figures

List of Tables

Introduction

Airbnb, founded in 2008, has become a prime example of the transformation within the lodging industry. The platform allows people to rent out their private properties—whether individual rooms or entire homes—providing guests with a more personalized experience and often offering competitive pricing (Guttentag, 2015). By December 31, 2023, Airbnb will be operating in more than 220 countries and regions, with over 1.5 billion guest arrivals, marking its significant role in shaping global tourism and the international lodging market (Airbnb, 2024). In addition, there are active listings in over 100,000 cities and towns across more than 220 countries, with more than eight million total advertised listings as of June 30, 2024.

Several dynamics within the sharing economy have fueled Airbnb's rapid ascent. The existence of new technologies: digitization and mobilisation, decrease the transaction cost associated with trust cooperation between strangers–of which peer-to-peer exchanges is an obvious example (Botsman & Rogers, 2010). The post-2008 global financial crisis further fomented mainstream acceptance of the sharing economy space as people searched for new ways to create or save money in challenging economic conditions (Edelman & Luca, 2014). Third, changing consumer tastes —of younger consumers who now favour the variety and flexibility offered by models such as Airbnb over established hotel types (Tussyadiah & Pesonen, 2016).

With that fast growth, however, have also come controversies and questions around Airbnb. Critics also claim that Airbnb worsens affordable housing crises by converting long-term residential units into tourist accommodations, which decreases the number of available rental listings in expensive urban centers (Horn & Merante, 2017). Furthermore, Airbnb is also highly illegal in most cities and concerns about tax evasion, safety negligence as well as the distortion of local communities have been raised (Zervas et al., 2017). Despite such challenges and increasing pressure for regulation, Airbnb (and other platforms in the sharing economy keeps growing raising new discussions on regulations as well as sustainable impacts over conventional hospitality industry along with medium to long-term effects.

The aim of this study is to analyse the efficiency of Airbnb's production function across different cities, examining changes over time and comparing productivity across Europe. Considering the significant impact Airbnb has had on the tourism and hospitality sectors, this research will gather data to evaluate how effectively each city manages varying levels of demand pressure.

To achieve this, the primary objective is to identify the proper inputs and outputs, as well as the right Data Envelopment Analysis (DEA) model to analyse Airbnb operations. Our analysis will not only identify the cities that perform efficiently but also set benchmarks for those that do not. In addition, the study will apply the Malmquist Productivity Index to follow performance trends, providing a clear and holistic view of the regional efficiency development within the Airbnb market.

To support this analysis, the structure of the dissertation is carefully designed. Chapter 2 begins with a review of the relevant literature, exploring the theories and research that underpin the study of Airbnb's impact. Building on this foundation, Chapter 3 outlines the methodology, with a focus on the DEA models and the Malmquist index, while also addressing the critical decisions regarding orientation, returns to scale, and the selection of variables. Chapter 4 then presents the dataset used for the analysis and discusses the detailed findings. Finally, Chapter 5 concludes the dissertation by summarizing the key insights, providing recommendations for strategic decision-making, and suggesting areas for future research.

1. Literature Review

This chapter explores theoretical concepts and empirical analyses on efficiency in economics and the hospitality sector. It begins with a discussion on efficiency in economic theory and the application of Data Envelopment Analysis (DEA). Following this, the impact of Airbnb on the hospitality sector is examined, analysing shifts in guest preferences and the regulatory and economic challenges faced by urban environments.

1.1 Theoretical Framework

This section will explore key models of efficiency that have shaped economic and business strategies. This division helps scaffold the understanding of theoretical concepts before applying them to the practical case of Airbnb in the hospitality sector

1.1.**1** The Concept of Efficiency in Economic Theory and Practice

Efficiency, as initially conceptualized by M. J. Farrell in 1957, fundamentally describes how well firms utilize resources to maximize outputs. Farrell proposed two main elements: allocative efficiency and technological efficiency. Allocative efficiency evaluates whether a company has used its resources as cost-effectively as feasible, striking a balance between costs and the value of the output generated, whereas technical efficiency examines a firm's capacity to produce the highest output from a given number of inputs. These distinctions have given economists and businesses a basic framework for further economic and operational evaluations, enabling them to more accurately assess the productivity and cost-effectiveness of different organisational activities (Farrell, 1957).

Building on Farrell's framework, Harvey the concept of X-efficiency, first introduced by Leibenstein in 1966, focused on internal organisational inefficiencies as opposed to those resulting from external market factors. The conventional neoclassical belief that businesses are inherently motivated to maximise profits through flawless operational efficiency was criticised by Leibenstein. Rather, he emphasised how internal variables that can result in less-than-ideal performance include a lack of drive, poor management techniques, and an ineffective company culture. This is especially true in settings where there is less pressure from competitors, as businesses may not be subject to the required market forces that require maximum efficiency. X-efficiency thus serves as a critical lens through which to view the real-world operational slack that can occur, explaining why firms might use more inputs than necessary to achieve a given output, or why they might fail to minimize costs as predicted by neoclassical theories. Furthermore, Leibenstein discussed how firms in imperfect market structures might engage in allocative inefficiency by setting prices that do not correspond to marginal cost, often due to monopolistic or oligopolistic conditions (Leibenstein, 1966).

Michael Porter, a leading figure in strategic management, connected these economic theories of efficiency with the competitive dynamics of industries. Porter argued that a firm's ability to achieve and sustain competitive advantage is intricately linked to its operational efficiency. He emphasized that firms must strategically align their resources and operations to effectively navigate competitive forces within the industry. According to Porter, strategic positioning—how a firm differentiates itself within the market—plays a crucial role in determining its efficiency. Firms that succeed in creating unique value propositions through efficient use of resources are better positioned to outperform their rivals (Porter, 1985).

In more contemporary economic theory, Subhash Ray brought a nuanced understanding of efficiency as a dynamic measure, not just a static benchmark. Ray argued that an efficient unit operates close to a theoretical or empirical benchmark—this benchmark can be derived from past performance metrics or industry standards, serving as a guiding star for operational improvement. This perspective suggests that efficiency is not merely about current performance but about continuous improvement and adaptation to changing operational conditions (Ray, 1997).

The theoretical concepts of efficiency discussed provide a foundation for practical methodologies used to assess efficiency in real-world settings. Among these methodologies, Data Envelopment Analysis (DEA) stands out as a tool that applies these theoretical concepts to measure efficiency across various contexts, including the hospitality sector.

1.1.2 Data Envelopment Analysis: A Tool for Assessing Performance in the Hospitality Sector

Data Envelopment Analysis (DEA) is widely recognized as a robust non-parametric methodology for assessing the efficiency of decision-making units (DMUs), such as hotels. This technique has been particularly effective in the hospitality sector where multiple input and output variables are involved (Cooper, Seiford, & Tone, 2000). Unlike parametric methods that assume a specific functional form for the production possibility frontier, DEA applies minimal assumptions, constructing a piecewise linear frontier from the data itself (Charnes, Cooper, & Rhodes, 1978).

Recent studies have further refined the application of DEA by incorporating a double bootstrap approach to correct biases inherent in traditional DEA estimates. For example, Assaf and Agbola (2011) utilized this approach to evaluate the technical efficiency of Australian hotels, revealing that factors such as location, years in business, and hotel size significantly influence efficiency. Their findings suggest that

DEA, coupled with bootstrapping, provides a more accurate reflection of true operational efficiency by addressing random errors and measurement inaccuracies typical in the DEA model (Assaf & Agbola, 2011).

The hospitality industry benefits from DEA's flexibility to handle various operational metrics. Studies such as those by Barros (2005) have applied DEA to explore the efficiency of hotels in different regions, underscoring the method's adaptability to diverse market conditions. These studies typically highlight the impact of external and internal factors on efficiency, ranging from global economic shifts to local management practices (Barros, 2005).

Furthermore, the application of DEA extends beyond traditional hotel settings. For instance, Morey & Dittman (1995) used DEA to benchmark the performance of US hotels, focusing on both financial and service-oriented outputs. This approach has proven invaluable in settings where output quality is as critical as operational cost efficiency.

Despite its advantages, DEA is not without limitations. The method assumes that all data points are accurate and does not account for potential data errors or external shocks that might affect the outputs and inputs (Banker, Charnes, & Cooper, 1984). Moreover, the reliance on historical performance data may not always predict future efficiencies accurately, particularly in fast-changing sectors like tourism.

In recent developments, the integration of DEA with other analytical methods such as Stochastic Frontier Analysis (SFA) and Malmquist Productivity Index has been explored to provide a more dynamic and comprehensive assessment of efficiency over time. For example, Färe, Grosskopf, Norris, and Zhang (1994) demonstrated how combining DEA with these methods could track efficiency and productivity changes across multiple periods, providing insights into long-term trends and shifts in performance benchmarks.

1.2 Empirical Insights and Analysis

This section presents empirical evidence to explore the transformative impact of platforms like Airbnb on economic behaviour, market dynamics, and consumer preferences within the hospitality industry.

1.2.1 The Sharing Economy Landscape

Through technology-driven platforms, the sharing economy allows individuals to share resources such as vehicles, residences, and services directly, thereby redefining the traditional concepts of access versus ownership. With online platforms facilitating the match between supply and demand, this economic paradigm enables people to access shared resources without the need for outright ownership (Zervas, Proserpio, & Byers, 2017).

Fundamentally, platforms that facilitate smooth peer-to-peer transactions underpin the sharing economy, often referred to as access-based consumption. Unlike traditional models where ownership is necessary for utilization, this model stands out for its ability to provide temporary access to goods and services (Möhlmann, 2015). By optimizing the use of underutilized assets, these platforms encourage a community of users who engage in more sustainable consumption, going beyond merely connecting buyers and sellers.

The success of sharing economy platforms like Airbnb and Uber illustrates a significant shift in consumer behavior, favoring convenience, cost-effectiveness, and a sense of community over the permanence of ownership. This shift is heavily influenced by digital transformation, which has broadened the reach and operational efficiency of sharing-based transactions (Gansky, 2010).

However, trust between consumers and service providers remains a crucial element of the sharing economy. Platforms must ensure reliable interactions and provide mechanisms to transact securely. Trust is built through transparent user reviews, robust platform policies, and active community engagement, which are essential for addressing the inherent risks of peer-to-peer interactions (Hawlitschek, Teubner, & Gimpel, 2016).

Despite its advantages, the sharing economy faces several challenges and criticisms. Issues such as regulatory concerns, impacts on traditional industries, and potential economic disruptions are frequently debated. Researchers and policymakers are particularly interested in how the growth of this economy affects economic patterns and the implications for future regulatory frameworks (Cohen & Kietzmann, 2014).

1.2.2 Disruptive Effects of Airbnb on the Hospitality Sector

As Airbnb continues its rapid expansion within the sharing economy, it profoundly alters the hospitality industry landscape. Studies such as those by Zervas, Proserpio, and Byers (2017) clearly demonstrate this impact, revealing significant declines in hotel revenues particularly in cities with high concentrations of Airbnb listings. During peak tourist seasons, these effects are even more pronounced as Airbnb's budget-friendly alternatives attract cost-conscious travelers away from traditional hotels.

Guttentag's (2015) analysis adds context to this image by illuminating how Airbnb's entry into the hospitality business has revolutionised the manner that lodging is offered. This change improves the entire visitor experience by providing more individualized, homely settings, and broadens the variety of lodging options. It particularly resonates with families and long-term travellers who often look beyond conventional hotel offerings for their stays.

This evolution in lodging options naturally extends to influence urban housing markets, as discussed by Barron, Kung, and Proserpio (2018). Their research indicates that Airbnb's integration into residential areas tends to drive up rental prices and squeeze the availability of long-term rentals. This not only alters the fabric of communities but also sparks debates around the sustainability of such shifts, particularly in cities like New York and San Francisco where the tension between short-term tourism benefits and long-term residential needs is most acute.

Further reflecting on the cultural shifts encouraged by Airbnb, Quattrone et al. (2016) observe a growing trend among travelers to seek accommodations that provide authentic local experiences. This drive towards 'living like a local' is gradually reshaping the competitive landscape, compelling traditional hotels to rethink their approach to hospitality to cater to this new demand for personalized experiences.

Dogru, Mody, and Suess (2019) expand on the economic challenges posed by Airbnb to different segments of the hotel industry, noting that while luxury establishments might weather the storm with minimal disruption, budget and mid-tier hotels are compelled to innovate aggressively. These hotels must adapt their strategies in pricing, marketing, and customer engagement to maintain relevance in an increasingly Airbnb-dominated market.

Echoing sustainability concerns, Gössling and Hall (2019) critically evaluate the long-term impacts of Airbnb's business model on local communities and infrastructures. They advocate for a balanced approach that weighs the economic advantages of Airbnb against the potential strains it places on local resources and living conditions.

1.2.3 Factors Influencing Guest Preferences for Airbnb

The rapid rise of Airbnb as a preferred accommodation option can be attributed to a variety of factors beyond just competitive pricing. According to Guttentag (2015), Airbnb offers a distinct value proposition compared to traditional hotels. While hotels may excel in areas like service quality and security, Airbnb attracts travelers through cost savings, household amenities, and the potential for a more authentic local experience.

Numerous studies have empirically investigated these motivations. For instance, Sthapit and Jiménez-Barreto (2018a) found that price and location are the primary drivers for Airbnb use among global users. Similarly, So et al. (2018) highlighted that economic benefits, enjoyment, and household amenities significantly influence attitudes towards Airbnb, impacting behavioral intentions. However, factors such as authenticity, social interaction, and the sharing economy ethos were found to have less impact. In contrast, Guttentag et al. (2018) revealed that while Airbnb's practical benefits (e.g., price, location, household amenities) are the main attraction for many users, experiential benefits like social interaction, authenticity, and novelty still hold value for a subset of guests. Paulauskaite et al. (2017) corroborate this by noting that cost savings and authenticity are key motivators, with authenticity encompassing the accommodations, interactions with hosts, and local cultural engagement.

Segmented analyses also provide deeper insights. Guttentag et al. (2018) conducted a cluster analysis revealing five distinct segments of Airbnb users based on their desire for social interaction and accommodation preferences. Boxall et al. (2018) specifically examined disabled travelers, noting that Airbnb's flexibility often better accommodates their needs compared to traditional hotels, although widespread availability would require government intervention.

Studies employing the Theory of Planned Behavior and the Theory of Reasoned Action have also shed light on factors influencing Airbnb usage. So et al. (2018) found that perceived behavioral control, trend affinity, and social influence positively affected intentions to use Airbnb, whereas perceived insecurity had a negative impact. Amaro et al. (2018) found that for Millennials, subjective norms, a preference for unique listings, and positive attitudes towards online shopping were significant drivers, with perceived economic benefits being less influential.

The perception of Airbnb's brand is also crucial. Early research by Yannopoulou et al. (2013) highlighted Airbnb's brand identity focusing on the everyday nature of hosts and the balance between authenticity and professionalism. Lee and Kim (2018a) found that users perceive Airbnb's brand as exciting, sincere, and competent, aligning with their experiences of originality, friendliness, and reliability. Yang et al. (2018) further revealed that trust in Airbnb's brand is often built through interactions with hosts and the credibility of individual listings.

Reviews play a pivotal role in Airbnb's success, as they help establish trust between guests and hosts. Abrahao et al. (2017) conducted an experiment involving thousands of Airbnb users, manipulating host demographics and reputations, and found that positive reviews effectively counteract biases arising from social distance. Their findings were supported by analyzing one million actual interactions on Airbnb. In a related study, Bae et al. (2017) surveyed South Korean Airbnb users and discovered that reducing social distance increased the perceived credibility of reviews, which in turn boosted purchase intentions.

Finally, comparing Airbnb guests with hotel guests offers additional insights. Volgger et al. (2018) found that Airbnb users are generally more likely to travel for pleasure and visit semi-peripheral regions, while Poon and Huang (2017) identified that Airbnb users tend to be older, more educated, and focused on price and security compared to hotel users.

When it comes to choosing specific Airbnb listings, several attributes have been identified as important. Gunter and Önder (2018) found that listing size, photo quality, and host response rates positively affect demand, whereas price and distance from the city center can deter potential guests. Research by Xie and Mao (2017) indicated that Superhost status, response rates, membership duration, and review attributes significantly influence demand. Liang et al. (2017) showed that guests are willing to pay a premium for stays with Superhosts, who are associated with higher ratings and positive reviews. Additionally, Abrate and Viglia (2017) found that verified identification, a Superhost badge, longer time on the platform, and higher review quantity boost host revenue, while Mauri et al. (2018) found that popularity, measured as a combination of rating scores, review quantity, and saved wish lists, was largely driven by reputation, which is impacted by personal narrative storytelling in hosts' self-descriptions.

Overall, while price remains a critical factor, the diversity of Airbnb's offerings, combined with perceived value and brand perception, makes it a compelling alternative to traditional hotels. The insights from these studies illustrate how Airbnb meets various needs and preferences, contributing to its growing popularity.

1.2.4 Regulatory and Economic Impacts of Airbnb on Urban Landscapes

The rapid expansion of Airbnb has profoundly influenced local economies, particularly through the transformation of housing markets and the emergence of complex regulatory challenges. Studies such as those by Wachsmuth and Weisler (2018) illustrate how Airbnb has contributed to gentrification by creating a new type of rent gap in desirable neighborhoods, transforming long-term housing into short-term rentals. This shift not only diminishes the availability of long-term housing but also escalates rents, thereby impacting the affordability and stability of communities.

Adding a quantitative view, Barron, Kung and Proserpio (2020) indicate that for every 1% increase in Airbnb listings there is a 0,018% increase in rents and a 0,026% increase in house prices, with these increases impacting areas with fewer owner-occupiers. In this way, non-owner-occupiers tend to change their properties from long-term to short-term rental markets, adding to local housing pressures. With Airbnb being an important actor in the sharing economy, it has challenged conventional economic ideas by providing a platform that involves peer-to-peer travelers directly with hosts, hitting high impacts on local economies. According to Sundararajan, 2016, this model shifted not only the dynamics of the local housing markets but also provided fuel for talking about updated regulations which would handle the unique challenges such platforms have raised. The model has shifted the dynamics of local housing markets and provided fuel for talking about updated regulations that would handle the unique challenges that such platforms have raised.

Municipal responses to Airbnb's growth have varied, with some cities implementing strict regulations or outright bans, partly to curb the rapid conversion of residential units into short-term rentals which, in turn, drives up local rents and strains affordable housing availability. Cities like Berlin and Barcelona have pursued aggressive policies against short-term rentals, citing the need to protect local housing markets and preserve community integrity (Wieditz, 2017).

Furthermore, cities face substantial hurdles when attempting to integrate Airbnb into existing legal frameworks. For instance, cities like New York and Barcelona have encountered significant legal challenges in balancing the economic benefits Airbnb brings with the need to protect long-term housing for residents. Guttentag (2017) details these complexities, noting the struggle to adapt regulatory environments to accommodate new business models that disrupt established industries and community norms.

Regulating Airbnb, as described by researchers like Oskam and Boswijk (2016), varies greatly depending on city size, established tourism industries, and the specifics of Airbnb listings. Traditional regulatory models often fall short because Airbnb operates as a peer-to-peer platform, necessitating a rethinking of conventional approaches (Espinosa, 2016). Regulations often target hosts rather than the platform itself, posing significant challenges in ensuring compliance (Edelman & Geradin, 2016).

The most common regulatory approach involves limiting Airbnb with a variety of restrictions: quantitative limits on the number of rentals, the number of guests or days a property can be rented, and the frequency of rentals per year (Guttentag, 2015; Miller, 2014). Locational and density restrictions might confine rentals to specific areas or limit the number of rentals in certain neighborhoods to prevent over-saturation (Gurran & Phibbs, 2017). Qualitative restrictions may dictate the type of accommodation offered and include safety requirements like smoke detectors.

It is crucial to recognize that not all cities should adopt the same regulatory strategy due to the varying impacts of Airbnb, which can depend on geographic location, the type of property rented out, and the destination's popularity (Gurran & Phibbs, 2017). While some cities may want to embrace Airbnb to boost tourism, others might choose to strictly regulate or even ban the platform to address local concerns, such as taxation or security issues (Oskam & Boswijk, 2016).

2. Methodology

This chapter presents a comprehensive overview of the methodologies applied in this study, including the Data Envelopment Analysis (DEA) model and the Malmquist Index. Additionally, it discusses the selection of appropriate returns to scale and the determination of the optimal orientation for the analysis.

2.1 Introduction to Efficiency and Productivity

Productivity Fundamentals

The concept of productivity in an economic setting involves converting inputs (like labour and materials) into outputs (products or services), a transformation first conceptualized by Cobb & Douglas in 1928. The most straightforward method to measure productivity involves calculating the ratio of output to input, expressed as:

$$\text{Productivity} = \frac{\text{Output}}{\text{Input}}$$

In this context, a firm acts as the primary decision-making entity, choosing how many inputs to utilize and outputs to generate. These decisions are constrained by the potential combinations of inputs and outputs available, termed the "production possibility set," which delineates the feasible output given the inputs. The outermost boundary of this set is known as the production possibility frontier, illustrating the maximum achievable outputs.

Understanding Technical Efficiency

Technical efficiency assesses the extent to which a given input combination maximizes outputs or minimizes inputs to achieve a specific output level. This efficiency can be viewed from two perspectives:

1. Input Technical Efficiency**:** Determines the minimum proportion by which inputs can be scaled down without reducing the output level. It is calculated as:

$$\text{Input Efficiency} = \frac{\text{Target Input}}{\text{Observed Input}}$$

2. Output Technical Efficiency**:** Identifies the maximum extent to which outputs can be increased with the available inputs. It is calculated as:

$$\text{Output Efficiency} = \frac{\text{Observed Output}}{\text{Target Output}}$$

The concept of returns to scale is crucial in understanding these efficiencies. Under constant returns to scale, both input and output efficiencies achieve parity. However, with variable returns to scale, these efficiencies diverge due to differences in scale efficiency, highlighting the complexity of optimizing both input use and output generation in diverse operational contexts.

2.2 Returns to Scale

In economic terms, returns to scale describe how output variations correlate with changes in input levels. This concept explores how output levels adjust when all inputs are scaled by a uniform percentage, a change that is predominantly driven by technological advancements. The phenomena of Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) delineate two distinct patterns of scale responses:

- Constant Returns to Scale (CRS): This scenario occurs when the increase in output is directly proportional to the increase in inputs. For instance, within a production framework involving two inputs and one output, an increase of inputs (x1, x2) by a factor of k results in an output increase by the same factor, symbolized as $ky = kf\,(x1, x2)$, where y represents the output, and x1 and x2 are the inputs.

- Variable Returns to Scale (VRS): Under VRS, the output's rate of increase does not match the proportional increase in inputs. This category is further divided into:

  a) Increasing Returns to Scale (IRS): Occurs when the total output increase surpasses the proportional input increase. In a specific production scenario, if all inputs (x1, x2) are scaled up by a factor k, the resulting output kyky will be greater than $ky > kf\,(x1, x2)$.

  b**)** Decreasing Returns to Scale (DRS): Happens when the output increases by a proportion smaller than that of the input increase. In such cases, increasing all inputs (x1, x2) by a factor k will result in a less than proportional output increase $ky < kf(x1, x2)$.

The selection between CRS and VRS models is influenced by the specifics of the input-output dynamics considered in the study and the methodological orientation of the DEA model being applied.

2.3 Operationalizing Efficiency with DEA

Data Envelopment Analysis (DEA) is a non-parametric method in operations research and economics for the estimation of production frontiers. It helps to encapsulate the efficiency of decision-making units (DMUs) when multiple input and output measurements are present. By using linear programming to frame a set of efficiency scenarios, DEA evaluates the relative efficiency of each unit without requiring predefined weights, allowing for an objective assessment across varied operations (Cooper, Seiford, & Zhu, 2004).

Basic DEA Model Application

The DEA model evaluates the efficiency of each decision-making unit (DMU) by maximizing a ratio of weighted outputs to weighted inputs. Here's a concise formulation.

Objective Function: Maximize efficiency by solving the ratio of weighted outputs to inputs.

$$\text{Maximize } \frac{\sum_{i=1}^{s} u_i y_{ij}}{\sum_{r=1}^{m} v_r x_{rj}}$$

Constraints:

- Efficiency Constraint: This constraint ensures that the calculated efficiency ratio for any DMU does not exceed 1, establishing a benchmark where a value of 1 indicates optimal efficiency:

$$\frac{\sum_{i=1}^{s} u_i y_{ik}}{\sum_{r=1}^{m} v_r x_{rk}} \leq 1 \text{ for all } k$$

- Non-Negativity Constraint: Weights are restricted to be non-negative, allowing only positive contributions to the efficiency score. A small positive value ϵ is used to prevent any weight from becoming zero, which ensures that all inputs and outputs have some impact on the efficiency score:

$$u_i, v_r \geq \epsilon > 0$$

The model aggregates input and output data into a single efficiency score by solving this linear program for each DMU. The weights ui and vr are determined as part of the optimization process, reflecting the relative importance of each input and output in achieving maximum efficiency. This methodical approach provides a clear, objective means to assess and compare the performance of entities with diverse operational scales and output-input mixes.

2.4 Advanced DEA Applications

The basic DEA model's inherent complexity can lead to an infinite number of solutions, complicating its practical application. To address these challenges, Charnes, Cooper, and Rhodes (1978) introduced a simplified linear programming model, known as the CCR model. This model streamlines the efficiency evaluation process by providing a more manageable framework for analysis. The CCR linear programming model is described as follows:

CCR model

$$\text{Max } \frac{\sum_{i=1}^{s} u_i y_{ij}}{\sum_{r=1}^{m} v_r x_{rj}}$$

$$\text{s.t. } \frac{\sum_{i=1}^{n} u_i y_{ik}}{\sum_{r=1}^{m} v_r x_{rk}} \leq 1, \qquad k = 1, 2, 3, \ldots, n$$

$$u_i,\ v_r \geq \varepsilon > 0, \qquad i = 1, 2, 3, \ldots, s, \quad r = 1, 2, ., m$$

In this model, the initial constraint ensures that the aggregate of weighted inputs for each DMUequals one, illustrating the input-orientation of the CCR model. This feature allows each DMU the flexibility to determine the most advantageous weights for its inputs and outputs. The secondary constraint, however, ensures that no DMU's efficiency score exceeds one, using the designated weights. If a DMU achieves a score of one, it is deemed efficient; scores below one indicates inefficiency. This method ensures that each unit is evaluated within the framework of its operational capacity and resource utilization. The dual form of the equation is given below:

$$\text{Min } \theta_j \qquad (\text{iv})$$

$$\text{s.t. } \sum_{j=1}^{n} \lambda_j x_{rj} \leq \theta x_{rjo} \qquad r = 1, 2, m$$

$$\sum_{j=1}^{n} \lambda_j y_{ij} \leq y_{io} \qquad i = 1, 2, s$$

$$\lambda_j \geq 0 \qquad j = 1, 2, n$$

In the model, θj represents the input efficiency for unit j at a specific output level, while λj serves as the interpolation multiplier for the decision-making unit (DMU) j. When λj equals 1, it indicates that DMU j positioned on the efficiency frontier, thus serving as a benchmark for other DMUs with a similar input-output configuration.

However, the CCR model has its limitations. It assumes that all DMUs operate under constant returns to scale, meaning they are functioning at an optimal scale. This assumption may not hold true in practice, as achieving optimal scale is often impractical. Consequently, the efficiency evaluation using the CCR model might not always be suitable. To address this issue, Banker et al. (1984) introduced an enhanced version of the CCR model by incorporating an additional variable u_0 to account for varying returns to scale.

BCC model

$$\text{Max } \sum_{i=1}^{s} u_i \, y_{ij} + u_o$$

$$\text{s.t. } \sum_{r=1}^{m} v_r x_{rj} = 1$$

$$\sum_{i=1}^{s} u_i \, y_{ik} - \sum_{r=1}^{m} v_r x_{rk} + u_o \leq 0 \quad k = 1, 2, 3, \ldots n$$

$$u_i, v_r \geq \varepsilon > 0, \qquad i = 1, 2, 3, \ldots, s, \; r = 1, 2, \ldots, m$$

In the revised model, the variable u_0 captures the impact of scale efficiency, reflecting how returns to scale affect the evaluation. This modification ensures that each DMU is compared only with those of a similar scale, thereby accounting for differences in operational scale. As a result, the technical efficiency measures derived from the BCC model are either equal to or exceed those obtained from the CCR model (Thanassoulis, 2001). The BCC model, named after its developers Banker, Charnes, and Cooper, provides a more flexible approach by adjusting for varying scales of operation.

2.5 DEA Orientation and Model Application

Data Envelopment Analysis (DEA) provides two main orientation options for assessing efficiency: input orientation and output orientation. Input orientation is aimed at reducing the quantity of inputs needed to achieve a specific level of output, while output orientation focuses on maximizing the output that can be achieved with a given set of inputs. The choice between these orientations hinges on the objectives of the analysis.

In scenarios where the focus is on managing the inputs effectively, an input-oriented DEA model is used. This approach is beneficial for evaluating how well inputs are being utilized to generate outputs. Conversely, when the objective is to enhance output levels without changing the input quantities, the output-oriented DEA model is more appropriate. This model is designed to assess how much output can be maximized given the available inputs.

Since this research is performance-oriented and looks for maximization of output from the available inputs, the output-oriented DEA model will be most applicable. This approach has seen successful applications in related research works of Zekan et al. (2019) and Zekan and Gunter (2021).

The output-oriented BCC DEA model by Banker, Charnes, and Cooper applies very well here because it is best used in determining technical output efficiency. In this instance, the optimization of the number of listings on Airbnb would be the variable of output that may vary in each distinct city. To have a good capture of this variation, the VRS model would be used to allow changes in scale efficiencies that correspond to the size of listings found in each city.

The formulation of the DEA model for this study is as follows:

$$\text{Max } \theta + \varepsilon\left(\sum_{r=1}^{m} s_r^- + \sum_{i=1}^{s} s_i^+ \right)$$

$$\text{s.t. } \sum_{j=1}^{n} \lambda_j x_{rj} + s_r^- = x_{ro} \qquad r = 1, 2, m$$

$$\sum_{j=1}^{n} \lambda_j y_{ij} - s_i^+ = \theta y_{io} \qquad i = 1, 2,$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad j = 1, 2, n$$

$$0 < \varepsilon \ll 1$$

$$\lambda_j \geq 0$$

In the DEA framework, the variables s^- and s^+ denote the slacks in inputs and outputs, respectively. The third constraint in equation (iv) addresses the concept of variable returns to scale, which reflects how efficiency changes with varying levels of inputs and outputs.

A crucial aspect of DEA is that Decision-Making Units (DMUs) should be comparable, meaning they must utilize similar types of inputs to generate comparable outputs (Thanassoulis, 2001). For this analysis, 30 European cities operating Airbnb listings have been selected as DMUs. This selection ensures that the study adheres to the homogeneity requirement of the DEA methodology.

Additionally, a common guideline for DEA variable selection is that the number of DMUs should be at least double or, preferably, triple the combined total of inputs and outputs. Given that this study uses a model with one input and two outputs, having data from 30 cities meets the recommended criteria for the analysis.

2.6 Malmquist Productivity Index

The Malmquist Productivity Index measures the evolution of total factor productivity (TFP) across two observations by comparing their relative distance to a common technological frontier (Estache et al., 2004). This measure incorporates shifts in technology boundaries and variations in efficiency levels. The pioneering application of this index in a DEA context was developed by Fare et al. (1992), who decomposed the index into two primary factors: boundary shifts, termed Technological Change (TC), and Efficiency Change (EC).

Technological Change reflects advancements or declines in the efficient frontier that affect the entire industry, indicating shifts in technology used by operational units. Efficiency Change, on the other hand, represents the shifts in how efficiently a unit operates relative to the evolving industry standard. The overall change in productivity, therefore, is calculated as the product of these two components:

$$MI = EC * TC$$

Where EC stands for the efficiency change component, and TC represents the technological shift. A value above 1 for the Malmquist Index indicates an improvement in productivity, whereas a value below 1 suggests a decline. If the index equals 1, it signifies no change in productivity between the two periods.

The methodology to adapt the Malmquist index for variable returns to scale (VRS) conditions was critiqued by Ray & Desli (1997), leading to further refinement. Under the VRS framework, while TC remains constant, EC is further divided into pure technical efficiency change (PEC) and scale efficiency change (SEC), enriching the index's interpretative power. The formula under VRS becomes:

$$MI = PEC * SEC * TC$$

This adaptation allows for more precise measurements of productivity changes under variable scale conditions. However, it's important to note that certain cross-period analyses may encounter feasibility issues due to the VRS assumption, echoing the challenges found in super-efficiency models under similar conditions.

3. Selection of Data and Analysis

This chapter initiates with an overview of the data gathering and manipulation methods utilized in this study. It then details the criteria for variable selection, complemented by summary statistics. The chapter wraps up with a discussion on the outcomes obtained from the Data Envelopment Analysis (DEA) and the Malmquist index models.

3.1 Extraction of Data

This dissertation is based on data obtained from the Inside Airbnb database 2024 and focuses on 30 important European cities: Amsterdam, Antwerp, Barcelona, Berlin, Brussels, Copenhagen, Dublin, Edinburg, Florence, Geneva, Lisbon, London, Lyon, Madrid, Mallorca, Milan, Naples, Oslo, Paris, Porto, Prague, Riga, Rome, Stockholm, Valencia, Venice, Vienna, Zurich, Ireland, and Malta. Each city is treated as a DMU. The Airbnb database is presented quarterly, and in this analysis, it considers the three quarters: December 2023, March 2024, and June 2024. Efficiency score of DEA model and Malmquist index was calculated by using PIM-DEA Version 3.2 software.

For each selected European city, comprehensive data was gathered into CSV files, encompassing various details such as the listing ID, host information, location, amenities, guest capacity range, reviews, booking rates, pricing, and availability. This study prioritizes an evaluation of overall city performance rather than individual listings. To facilitate this, city-wide data summaries were generated using Python to calculate averages for all metrics, except for the total number of listings. This methodology aligns with insights from Zekan et al (2019), who emphasized the importance of average values for enabling comparisons across different cities. The analysis was confined to listings that were actively booked within the specified period, explicitly excluding any listings that were unbooked or listed at zero price.

3.2 Selection of the Variables

Choosing the appropriate input and output variables is a critical step in deploying a DEA model. The dataset provides various variables, but for this analysis, only specific inputs and two outputs were selected, guided by prior research in Airbnb benchmarking such as the studies by Zekan et al. (2019) and Gunder and Onder (2017). This study employs a DEA model that incorporates one input and two outputs to evaluate the data effectively.

Input

For this study, the input variable selected is the total number of Airbnb listings per city. This metric is crucial for assessing market density and potential saturation within individual urban Airbnb markets. According to research by Gunder and Onder (2017), a higher number of listings can indicate increased market activity, attracting more guests due to a wider variety of options. This phenomenon is exemplified by cities like Paris, where, according to Statista in 2023, the sheer volume of Airbnb listings reflects its status as one of Europe's largest markets for the platform. This distinction not only enhances Paris's appeal to international tourists but also significantly boosts demand and visibility.

Outputs

One of the key metrics analysed in this research is the monthly average revenue generated by each city's listings, represented in US dollars. This output variable quantifies the financial performance of Airbnb listings within each city. To compute the monthly average revenue, the study employs a formula that multiplies the average rate per booking by the total number of bookings recorded for each month. Additionally, the occupancy rate serves as another crucial output measure, calculated by dividing the number of days a property is booked by the total days in the month, providing insights into the utilization rate of Airbnb properties in each city. This approach provides a comprehensive view of how cities are leveraging their Airbnb market.

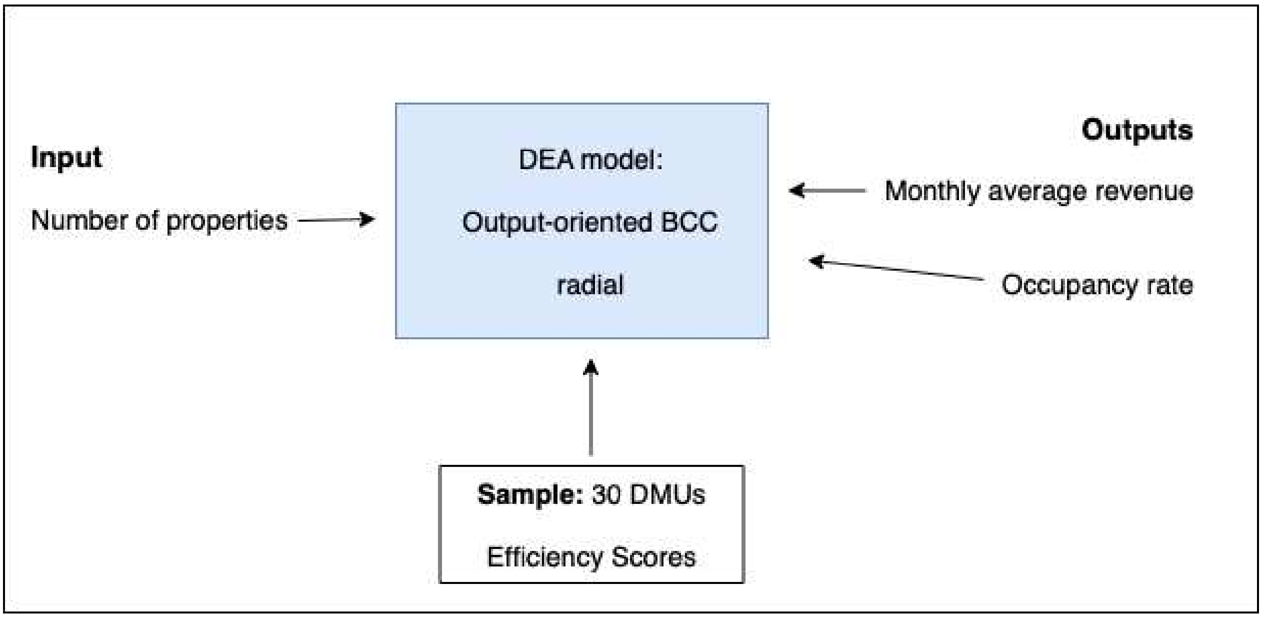


Figure 1: DEA Model Proposed

(*Source: An elaboration from Zekan and Gunter, 2021*)

3.3 Summary statistics of the inputs and outputs

For a clearer understanding of the variables involved in this study, descriptive statistics are detailed in Table 1, which outlines the distributions and central tendencies of the input-output variables.

Table 1: Descriptive statistics for the DEA model's variables

	Mean	Std. Dev	Min	Max
Input				
Number of Properties	15241	18406	2127	87589
Outputs				
Monthly Average Revenue	1254.22	2432.26	61.06	12128.39
Occupancy Rate	48.9	8.95	31.59	73.03

The dataset analysed contains an average of 15,241 Airbnb listings per city, with significant variability indicated by a standard deviation of 18,406. This highlights substantial differences in the size of Airbnb markets across different cities. The monthly average revenue per city stands at USD 1,254.22, although it varies widely from as low as USD 61,06 to as high as USD 12,128.39, demonstrating the diverse economic scales within these markets.

Additionally, the occupancy rates average 48,9%, with a standard deviation of 8,95%, reflecting moderate fluctuations across different markets. The range of occupancy rates spans from a minimum of 31,59% to a maximum of 73,03%, underscoring the varying levels of market saturation. Given the study's focus on comparing Airbnb listing performance across cities (referred to as sector benchmarking) the broad variance in the number of properties and their performance metrics is less of a concern, as the primary objective is not destination benchmarking but rather assessing relative operational efficiency within the sector.

3.4 Analysis of model outcomes

Table 2 outlines the summary statistics for the output-oriented pure technical efficiency scores from the DEA VRS model applied to Airbnb listings across 30 European cities. Each city name in the table corresponds to all active listings within that location.

Table 2: VRS Efficiency Distribution Across all DMUs

DMU	Mean	Std Dev	Min	Max
Amsterdam	99.64	0.50	98.93	100
Antwerp	79.99	9.78	73	93.82
Barcelona	75.49	5.15	68.74	81.24
Berlin	72.76	5.52	66.28	79.78
Brussels	76.26	6.40	70.6	85.21
Copenhagen	97.60	3.39	92.8	100
Dublin	82.48	3.45	78.4	86.83
Edinburgh	98.34	1.51	96.35	100
Florence	75.10	8.24	65.36	85.52
Geneva	100.00	0.00	100	100
Lisbon	70.27	7.17	61.12	78.63
London	69.18	9.72	57.94	81.65
Lyon	68.84	9.31	61.53	81.97
Madrid	69.15	3.78	63.85	72.42
Mallorca	79.56	12.28	67.57	96.43
Milan	57.39	0.91	56.11	58.13
Naples	52.95	6.85	43.26	57.93
Oslo	78.96	5.98	71.13	85.63
Paris	81.58	10.41	67.27	91.73
Porto	65.03	7.41	56.57	74.62
Prague	100.00	0.00	100	100
Riga	70.43	6.13	61.91	76.09
Rome	69.36	7.92	59.16	78.46
Stockholm	100.00	0.00	100	100
Valencia	69.54	3.26	67	74.14
Venice	77.04	7.46	67.04	84.96
Vienna	68.50	5.43	63.47	76.04
Zurich	95.72	5.20	88.4	100
Ireland	67.12	7.68	60.81	77.93
Malta	63.02	14.95	45.91	82.33

In the overview of output-oriented pure technical efficiency scores provided for Airbnb listings in 30 European cities, we observe stark contrasts in performance. Amsterdam, Copenhagen, Geneva, and Prague each scored a perfect average efficiency of 100% with zero variability, illustrating their consistent ability to maximize outputs under various conditions.

On the other end of the spectrum, Naples displays considerable room for improvement with an average efficiency score of 52,95%, indicating that it could enhance output by nearly 47,05% using the same inputs. This city also recorded the lowest efficiency score at 43,26%, highlighting significant operational inefficiencies.

Additionally, cities like Mallorca, Paris, and Malta show substantial fluctuations in their efficiency scores, with standard deviations of 12,28, 10,41, and 14,95, respectively. This variability suggests that while some listings perform excellently, others lag significantly, possibly due to seasonal shifts in tourism, competitive dynamics, or management variations within the Airbnb market. Such insights could guide strategic adjustments in pricing, marketing, and customer engagement to bolster overall efficiency.

The dataset has been segmented into two categories based on their average efficiency scores. The first category encompasses DMUs scoring between 76% and 100%, indicating high performance, while the second category covers those scoring from 50% to 75%, reflecting moderate performance levels. This classification is detailed in Table 3, which outlines the range and grouping of the DMUs based on their efficiency scores.

Table 3: Classification of DMUs Based on Average Efficiency Scores

Group 1 **(Average ES: ≥ 75%)**	**Group 2** **(Average ES: <74%)**
DMUs: 16	DMUs: 14
Amsterdam	Berlin
Antwerp	Lisbon
Barcelona	London
Brussels	Lyon
Copenhagen	Madrid
Dublin	Milan
Edinburgh	Naples
Florence	Porto
Geneva	Riga
Mallorca	Rome
Oslo	Valencia
Paris	Vienna
Prague	Ireland
Stockholm	Malta
Venice	
Zurich	

The efficiency of Airbnb listings across 30 European cities has been categorized into two groups based on the output-oriented pure technical efficiency scores derived from the DEA VRS model. Group 1 encapsulates cities exhibiting higher performance, with average efficiency scores ranging from 76% to 100%. This group includes cities like Amsterdam, Geneva, and Stockholm, which demonstrate robust operational efficiency. Conversely, Group 2 includes cities such as Berlin, Lisbon, and Milan, where efficiency scores vary between 50% and 75%, indicating opportunities for

operational enhancement. This classification highlights the performance disparities across various urban markets and pinpoints areas requiring targeted improvements. Further insights are gleaned from the efficiency trajectories of cities in Group 1, depicted in Figure 5. Throughout the period from December 2023 to June 2024, these cities generally displayed an upward trend in efficiency levels. For instance, Geneva consistently achieved high efficiency, culminating in full efficiency by June 2024. Similarly, Oslo exhibited remarkable growth, escalating from an efficiency score of 80,12% in December 2023 to 85,63% by June 2024, which reflects the city's resilience and adaptability amidst changing market conditions. However, some fluctuations were observed, such as in Paris, where efficiency decreased from 91,73% in December 2023 to 67,27% in June 2024, highlighting sporadic operational challenges. Despite these variations, the analysis confirms that most cities in Group 1 maintained or enhanced their efficiency, effectively mitigating significant negative impacts from external disruptions

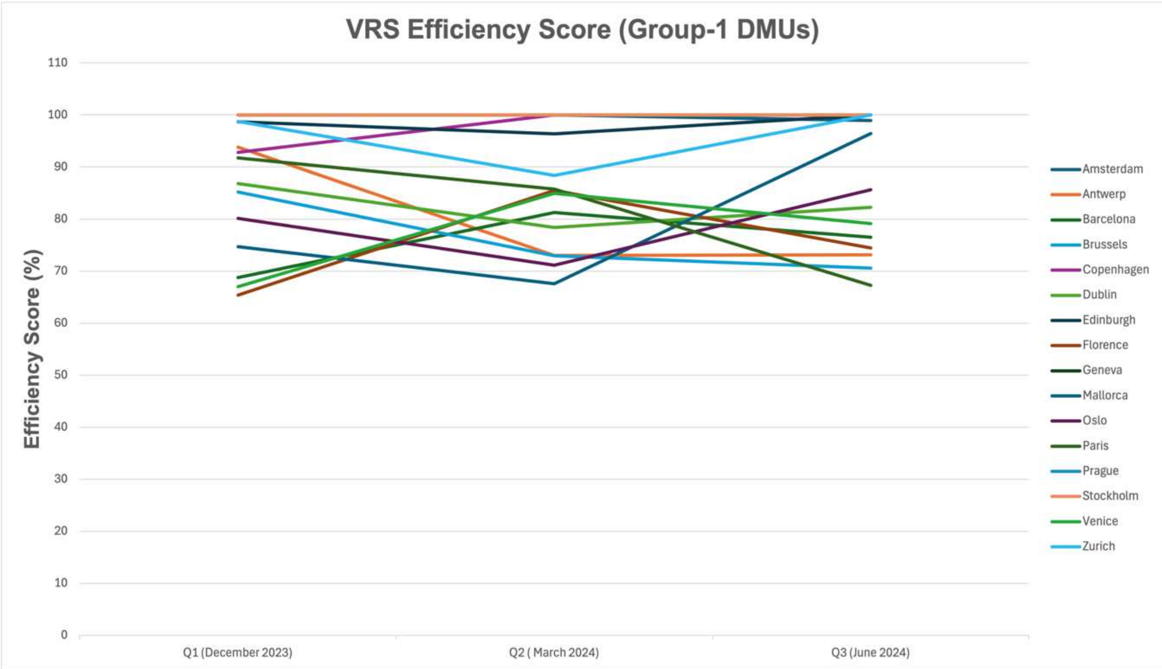


Figure 2: Output-Oriented VRS Efficiency Scores for Group-1 DMUs

Figure 6 captures the evolving efficiency scores for selected cities within Group 2 across three quarters. The visual representation highlights notable trends and deviations in efficiency levels. For instance, Berlin shows a steady increase in efficiency from 66,28% in December 2023 to 79,78% by June 2024, reflecting gradual improvements in operational performance. Similarly, Lisbon and Malta exhibit upward trajectories, with Lisbon jumping from 61,12% to 78,63% and Malta making a significant leap from 45,91% to 82,33% across the observed periods. However, not all cities followed this pattern. Milan and Madrid experienced fluctuations, with Milan showing minimal change and Madrid peaking in the first quarter before declining.

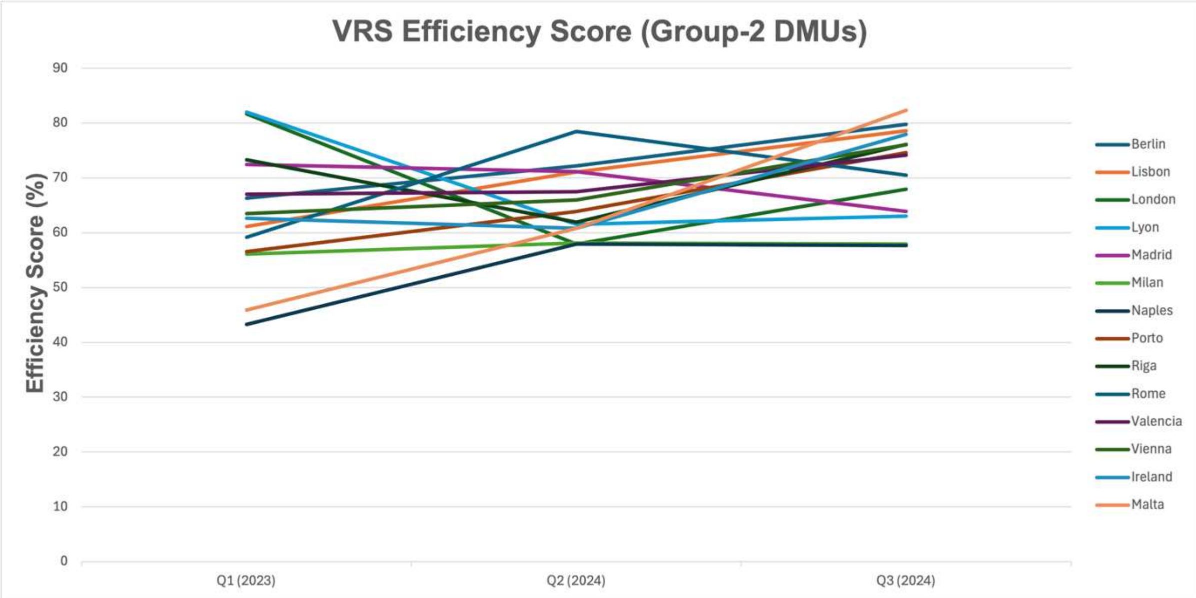


Figure 3: Output-Oriented VRS Efficiency Scores for Group-1 DMUs

3.5 Benchmarking Insights

3.5.1 Comparative Analysis of Airbnb Listings

The benchmarking of inefficient DMUs is determined for the most recent month in the dataset, June 2024. Therefore, the efficient referents or peers are identified based on this month alone. From the data in the table, we can observe that Naples is one of the least efficient DMUs, with an efficiency score of 57,65%, indicating that at least one of its outputs must increase by 42,35% while keeping the same level of input to achieve full efficiency. Naples has two benchmark partners: Copenhagen, with a lambda weight of 0,61, and Edinburgh, with a weight of 0,39. This means that Copenhagen serves as the more influential referent for Naples.

Table 4: June 2024 Efficiency Scores and Peer Comparisons for Inefficient Units

Inefficient DMUs	**Efficiency Scores**	**Efficient referents (Peers) with lambdas**					
		Copenhagen	Edinburgh	Geneva	Prague	Stockholm	Zurich
Amsterdam	98,93	0,1	0,9				
Antwerp	73,16		0,04				0,96
Barcelona	76,5	1					
Berlin	79,78	0,44	0,56				
Brussels	70,6	0,08	0,92				
Dublin	82,22	0,01	0,99				
Florence	74,42	0,8	0,2				
Lisbon	78,63	1					
London	67,94	1					
Lyon	63,01	0,08	0,92				
Madrid	63,85	1					
Mallorca	96,43	1					
Milan	57,92	1					
Naples	57,65	0,61	0,39				
Oslo	85,63	0,3	0,33		0,37		
Paris	67,27	1					
Porto	74,62	0,9	0,1				
Riga	76,09		0,11				0,89
Rome	70,47	1					
Valencia	74,14	0,47	0,53				
Venice	79,13	0,26	0,74				
Vienna	76,04	0,72	0,28				
Ireland	77,93	1					
Malta	82,33	0,77	0,23				

Additionally, Milan shows an efficiency score of 57,92%, requiring an increase in outputs by 42,08% to reach full efficiency. Milan has only one peer, Copenhagen, acting as the referent for this DMU with a weight of 1, indicating it plays a crucial role in guiding Milan toward efficiency. Lyon also shows inefficiency, with a score of 63,01%. It relies on two referents, Edinburgh (with a weight of 0,92) and Copenhagen (with a weight of 0,08), with Edinburgh being the dominant benchmark partner. The DMU with the highest efficiency score, Amsterdam, is close to achieving full efficiency with a score of 98,93%, indicating that only a minimal improvement is needed. As this analysis utilizes the Variable Returns to Scale (VRS) model, the lambda weights for each inefficient DMU add up to 1, maintaining the convexity condition.

Table 5: Benchmark Profiles of Efficient DMUs in June 2024

Efficient DMUs	Frequency
Copenhagen	**23**
Edinburgh	**16**
Geneva	**1**
Prague	**2**
Stockholm	**1**
Zurich	**3**

As Zekan et al. (2019) noted, not all efficient DMUs in a DEA model serve as benchmarks for inefficient units. This is clearly seen with Geneva and Stockholm, which, despite being efficient, have not played a significant role in guiding other inefficient DMUs, each appearing only once. Similarly, Prague and Zurich contribute minimally with only two and three appearances, respectively. In contrast, the benchmarking process is driven primarily by a few dominant DMUs, with Copenhagen and Edinburgh emerging as the most frequent benchmarks, appearing 23 and 16 times, making them the key references for performance improvement.

3.5.2 Analysis of Least Efficient Cities

The virtual benchmarking for the Naples listings was conducted using the PIM-DEA software. With an efficiency score of 57,65%, this DMU is considered inefficient in terms of output performance. Although there is no input slack (since the number of listings remains at 10,247), there is a notable output slack in the monthly average revenue, which stands at $3621,85.

Period q3 Selection <All> Categorical <All>

DMU B17
Efficiency 57.65%
Omega -0.99
Peers B6 (0.61), B8 (0.39)

Name	Number of Listings	Monthly Average Revenue (USD)	Occupancy Rate (%)
Type	Input	Output	Output
Actual	10247	749.43	39.8
Target	10247	4921.75	69.03
Slack	0	3621.85	0
Weight	0	0	0.03

Figure 4: Summary Overview of Naples Listings

The target for monthly revenue is set at $4921,75, requiring an increase from the current $749,43 to reach full efficiency. Similarly, the occupancy rate needs to improve from 39,8% to the target of 69,03%. This significant gap indicates that Naples has room to boost its performance in these areas to achieve optimal efficiency.

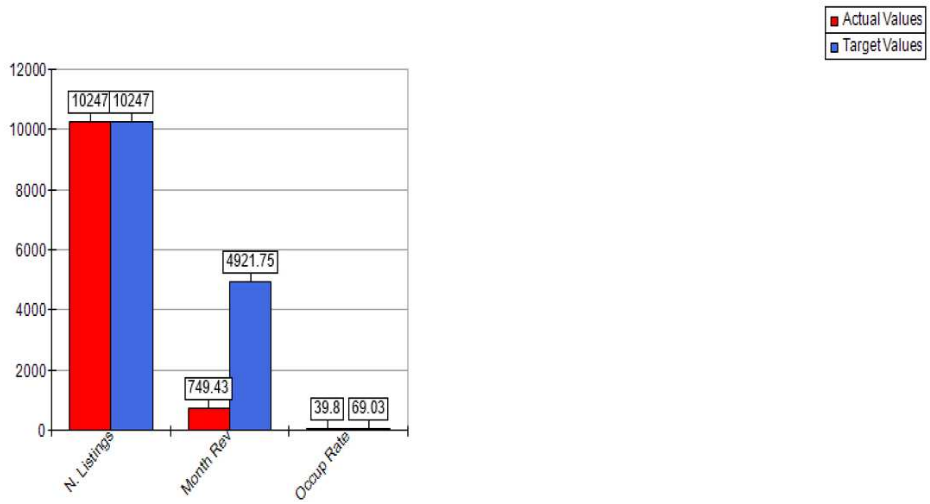
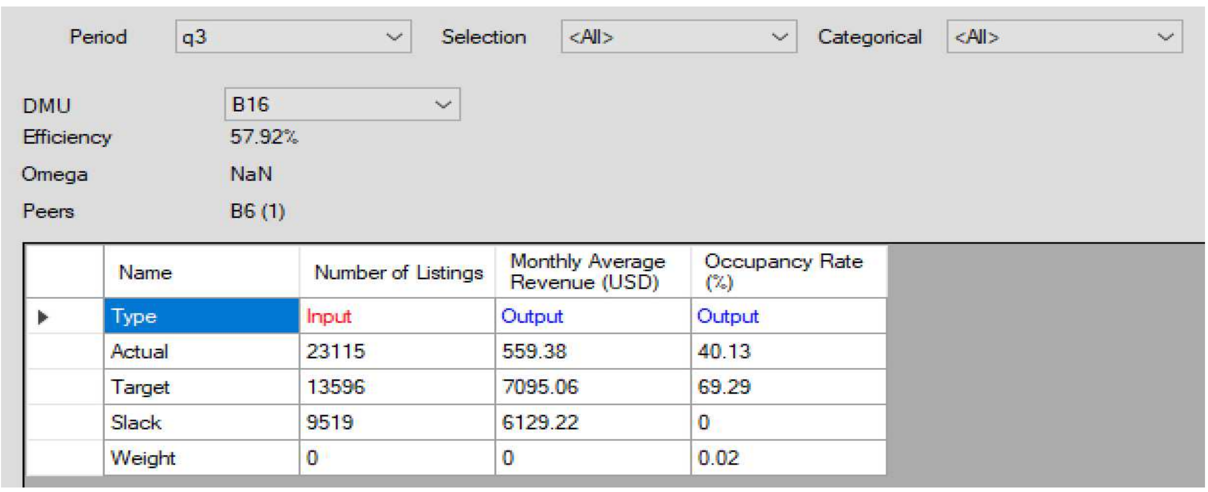


Figure 5: Comparison of Actual and Target Listing Values for Naples

The Milan listings have an efficiency score of 57,92% under the VRS DEA model, which suggests there is room for improvement in both the input (number of properties) and output (monthly revenue). As shown in Figure 10, this decision-making unit (DMU) has a positive slack for both inputs and outputs. This indicates that the number of properties and monthly revenue can both be optimized to improve efficiency.


Period q3 Selection <All> Categorical <All>

DMU B16
Efficiency 57.92%
Omega NaN
Peers B6 (1)

Name	Number of Listings	Monthly Average Revenue (USD)	Occupancy Rate (%)
Type	Input	Output	Output
Actual	23115	559.38	40.13
Target	13596	7095.06	69.29
Slack	9519	6129.22	0
Weight	0	0	0.02

Figure 6: Summary Overview of Milan Listings

The target monthly revenue is set at $7,095.06, which is significantly higher than the current actual revenue of $559,38. This large gap highlights the need for substantial improvements in revenue generation. Similarly, the target occupancy rate is 69,29%, while the actual rate is 40,13%. Achieving these target values would greatly enhance the operational efficiency, moving closer to the goal of 100%. Reaching the targets for both revenue and occupancy rate is essential for optimizing the overall performance.

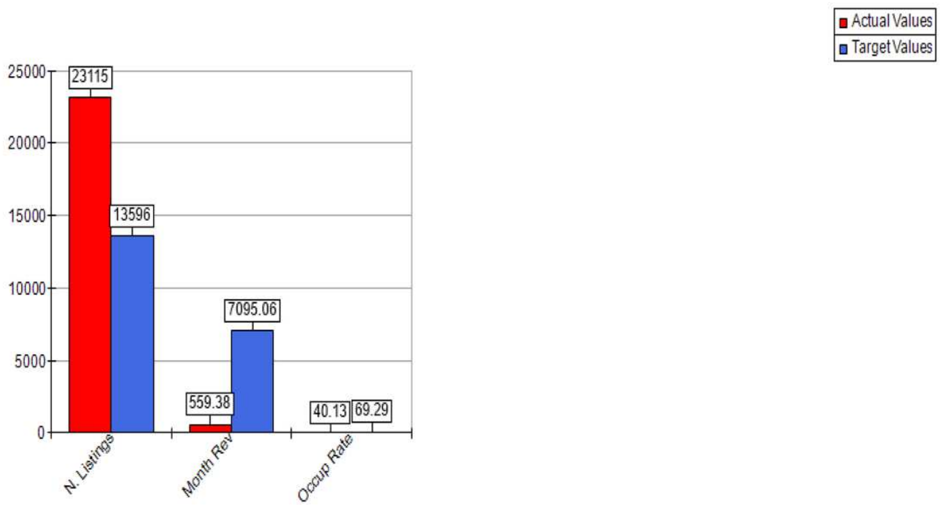


Figure 7: Comparison of Actual and Target Listing Values for Milan

The third least efficient DMU, Lyon, holds an efficiency score of 63,01% under the VRS DEA model, which highlights the opportunity to improve its output performance while maintaining the same number of properties. With 5,703 listings, the key area for enhancement lies in monthly revenue,
where Lyon falls significantly short.

Period: q3 | Selection: <All> | Categorical: <All>

DMU: B13
Efficiency: 63.01%
Omega: -0.99
Peers: B6 (0.08), B8 (0.92)

Name	Number of Listings	Monthly Average Revenue (USD)	Occupancy Rate (%)
Type	Input	Output	Output
Actual	5703	144.25	43.27
Target	5703	1972.95	68.67
Slack	0	1744.01	0
Weight	0	0	0.02

Figure 8: Summary Overview of Lyon Listings

Currently, Lyon's monthly average revenue is $144,25, far below the target of $1,972,95, indicating a gap of $1,744,01. Likewise, the occupancy rate stands at 43,27%, whereas the target rate is 68,67%. Bridging these differences in revenue and occupancy is crucial for Lyon to increase its efficiency score and approach full potential.

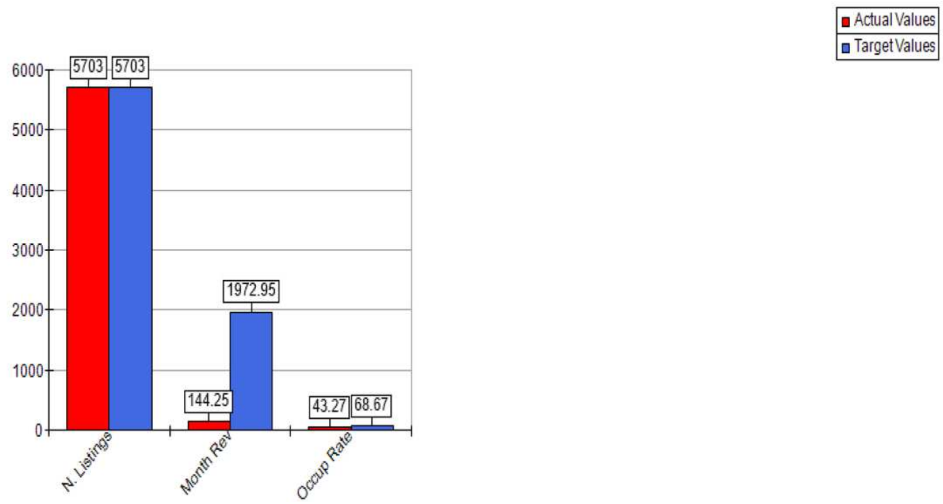


Figure 9: Comparison of Actual and Target Listing Values for Lyon

3.6 Malmquist Productivity Index

To evaluate the productivity changes over time for the Airbnb listings across European cities, Malmquist indices were calculated using the Ray & Desli Malmquist Index Function within the PIM-DEA software. Given that the VRS DEA model was employed in this analysis, this method is deemed the most suitable for the dataset. The Malmquist indices provide insights into the productivity trends for the different categories of DMUs, as outlined in the Base DEA model analysis, and are used here to assess the performance of Airbnb listings across European cities over the study period.

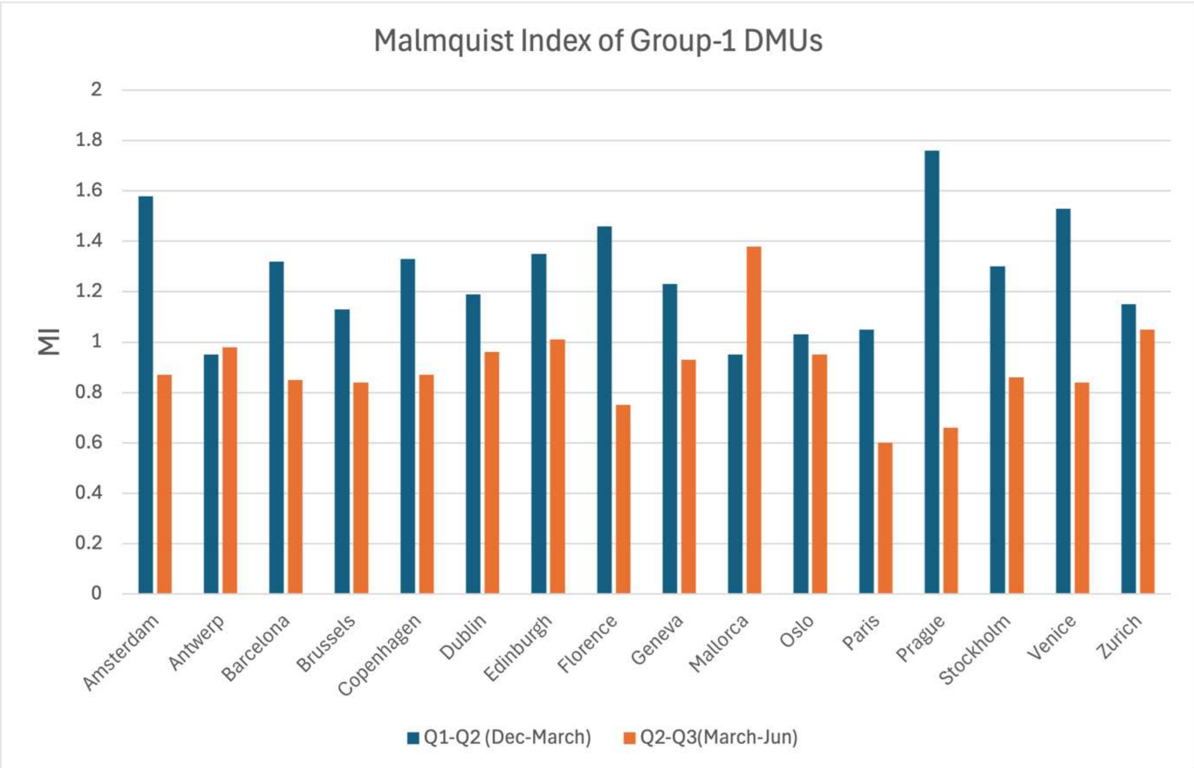


Figure 10: Malmquist Index of Group 1

The productivity trends across Group-1 cities predominantly show a decline from Q1-Q2 (Dec-March) to Q2-Q3 (March-June). While a few cities, such as Mallorca, demonstrated growth during the second period, the majority, including Amsterdam, Florence, and Prague, experienced significant drops in productivity. This widespread decline highlights the challenges cities face in sustaining high performance, which could be influenced by seasonal demand, market saturation, or operational inefficiencies. These results emphasize the importance of adaptive strategies to maintain competitive productivity levels over time.

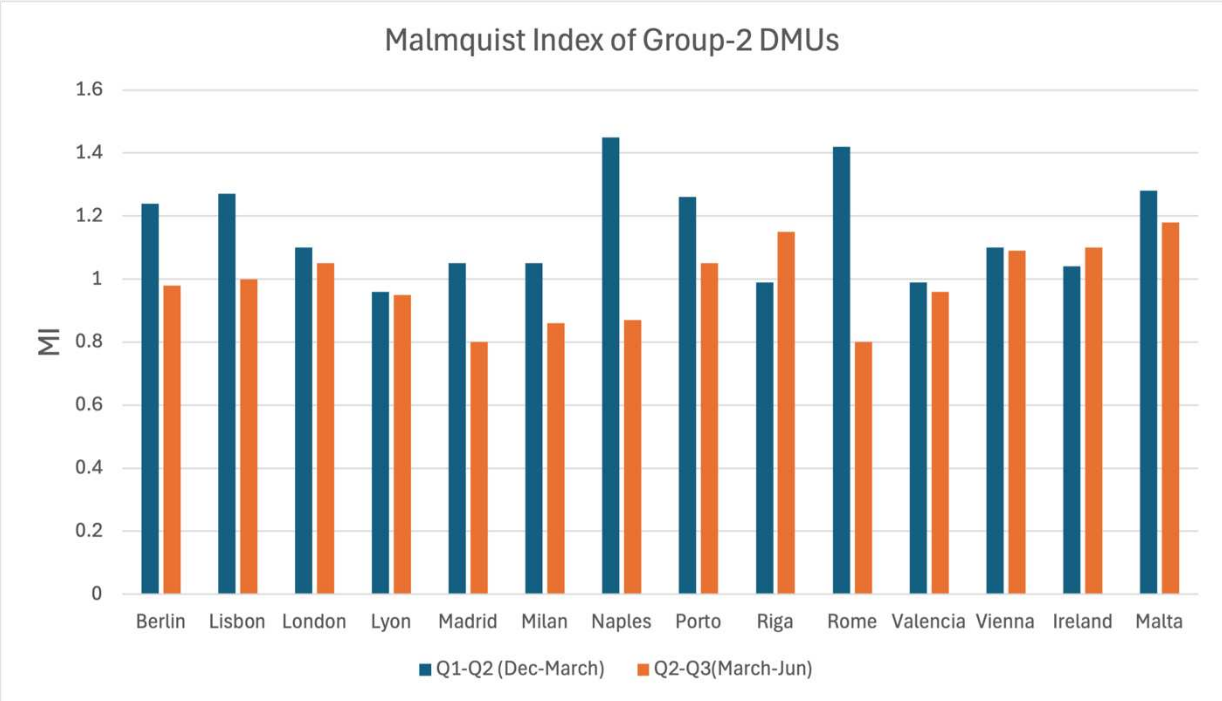


Figure 11: Malmquist Index of Group 2

For Group-2 cities, the productivity trends reveal that most cities experienced a decline from Q1-Q2 (Dec-March) to Q2-Q3 (March-June). Riga stands out as the exception, showing growth in its Malmquist Index (MI) during the second period, while cities like Rome, Naples, and Milan saw a significant drop in productivity. This overall decline suggests that most cities faced challenges in maintaining or improving their performance as the period progressed.

Table 7 presents the average Malmquist Index for all city listings over the entire period. According to the data, Malta have shown the highest average productivity growth, with an index of 1,23. In contrast, Paris has experienced the most significant decline in productivity, with an average index of 0,83, indicating a downward trend. These results suggest that while some cities have been able to enhance their efficiency and productivity over time, others have struggled to maintain performance.

Table 6: Comparative Analysis of Average Malmquist Productivity Indices

Group 1		Group 2	
DMU	MI	DMU	MI
Amsterdam	1,22	Berlin	1,11
Antwerp	0,97	Lisbon	1,14
Barcelona	1,09	London	1,08
Brussels	0,99	Lyon	0,96
Copenhagen	1,10	Madrid	0,93
Dublin	1,08	Milan	0,96
Edinburgh	1,18	Naples	1,16
Florence	1,11	Porto	1,16
Geneva	1,08	Riga	1,07
Mallorca	1,17	Rome	1,11
Oslo	0,99	Valencia	0,98
Paris	0,83	Vienna	1,10
Prague	1,21	Ireland	1,07
Stockholm	1,08	Malta	1,23
Venice	1,19		
Zurich	1,10		

A detailed analysis of the productivity changes for listings in Malta and Paris is discussed in the following sections.

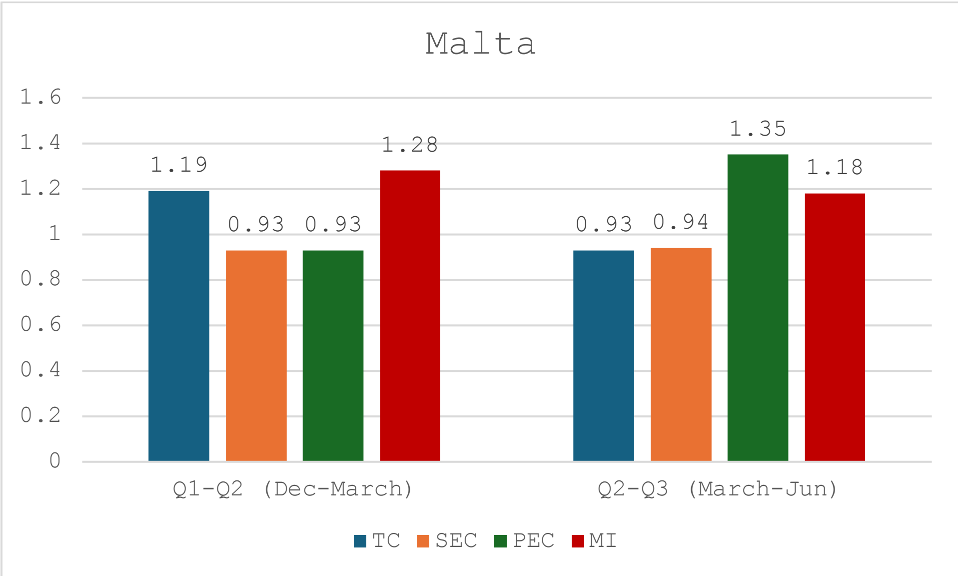


Figure 12: Evaluation of Technical Change and Efficiency Patterns in Malta Airbnb Listings

From figure 18, Malta's listings experienced significant progress in Q2-Q3 (March-June), primarily driven by an increase in pure efficiency catch-up (PEC), which rose from 0,93 to 1,35. Throughout the entire period, scale efficiency change (SEC) remained constant at 0,93, suggesting that scale efficiencies did not contribute to the overall productivity improvement. Technical change (TC) remained stable at 0,93 across both periods, indicating that technical advancements had little impact on the Malmquist Index, which saw a slight decline from 1,28 to 1,18 in the later period.

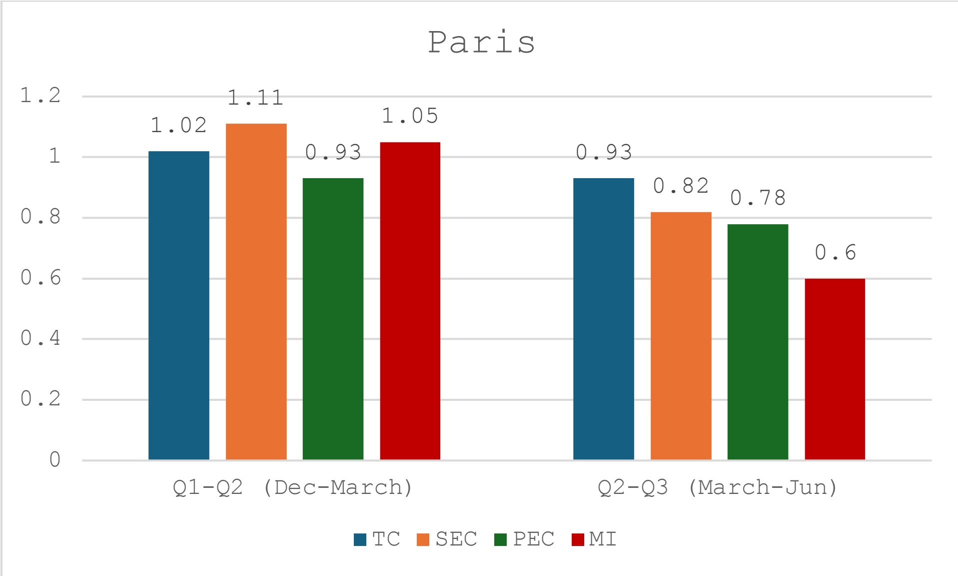


Figure 13: Evaluation of Technical Change and Efficiency Patterns in Paris Airbnb Listings

The Malmquist Index of Paris listings show a significant decline in Q2-Q3 (March-June), primarily due to drops in both pure efficiency catch-up (PEC) and scale efficiency change (SEC). The PEC decreased from 0,93 in Q1-Q2 to 0,78, while SEC fell from 1,11 to 0,82. These combined reductions in efficiency led to the sharp decline in the Malmquist Index (MI), which dropped to 0,6, reflecting a considerable reduction in overall productivity for Paris during this period.

4. Conclusion

This study assessed the performance of Airbnb listings across major European cities between December 2023 and June 2024. Using a dataset from 30 European countries, the DEA model was applied to calculate efficiency scores, with Number of Listings as the input and Monthly Average Revenue and Occupancy Rate as outputs. Additionally, the Malmquist Index was used to track productivity changes over the study period.

The results identified Geneva, Prague, and Stockholm as the most efficient cities, demonstrating strong resource utilization and consistently high outputs relative to their inputs. These cities' operational efficiency underscores well-optimized practices, positioning them as top performers.

Conversely, Naples was identified as the least efficient city. Despite having a stable number of listings, Naples faced inefficiencies in revenue generation and occupancy rates, indicating significant potential for improvement. Aligning its strategies with those of more efficient cities could help Naples close the performance gap.

In terms of benchmarking, Copenhagen and Edinburgh emerged as key peers. Though not the most efficient, they frequently served as benchmarks for less efficient units. This consistent role emphasizes that leadership in the short-term rental market is not solely determined by efficiency scores, but also by operational reliability and the ability to guide others toward improvement.

When considering productivity growth, Malta stood out with the highest average progression rate, despite being among the less efficient cities by June 2024. This suggests that while Malta has not yet reached full efficiency, it has made substantial strides in improving its performance, demonstrating potential for continued growth.

A significant observation from the analysis is that most cities experienced a decline in productivity during the study period. This widespread drop points to the challenges cities face in maintaining high performance, likely due to factors such as seasonal demand fluctuations, market saturation, or internal inefficiencies.

However, these findings should be interpreted considering the study's limitations. One limitation is the short timeframe, covering just seven months, which may not fully capture long-term trends or the full spectrum of seasonal variations in the Airbnb market. Additionally, the use of quarterly data, rather than monthly, limits the granularity of the analysis. More frequent data points might have provided a clearer view of the cities' performance trends, allowing for a more detailed understanding of fluctuations within the rental market. Moreover, the focus on a limited set of variables restricts the scope of insights into other factors that may influence efficiency.

Finally, time constraints further curtailed the ability to explore these issues comprehensively.
Despite these limitations, this study offers important insights into the dynamic performance of Airbnb listings across Europe. It highlights the need for cities to adopt adaptive strategies to remain competitive in an evolving short-term rental market. Understanding the strengths and weaknesses of both efficient and inefficient cities provides valuable guidance for future performance optimization.

References

Abrate, G., & Viglia, G. (2017). Personal or product reputation? Optimizing revenues in the sharing economy. *Journal of Travel Research, 58*(1), 136-148.

Abrahao, B., Parigi, P., Gupta, A., & Cook, K. S. (2017). Reputation offsets trust judgments based on social biases among Airbnb users. *Proceedings of the National Academy of Sciences, 114*(37), 9848-9853.

Airbnb. (2024). About us. Retrieved from https://www.airbnb.com/about

Amaro, S., Andreu, L., & Huang, S. (2018). Millennials' intentions to book on Airbnb. *Current Issues in Tourism*, 1-15.

Assaf, A., & Agbola, F. W. (2011). Modelling the performance of Australian hotels: A DEA double bootstrap approach. *Tourism Economics, 17*(1), 73-89.

Bae, J., & Koo, D. M. (2017). Lemons problem in collaborative consumption platforms: Different decision heuristics chosen by consumers with different cognitive styles. *Internet Research, 28*(3), 746-766.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078-1092.

Barron, K., Kung, E., & Proserpio, D. (2018). The sharing economy and housing affordability: Evidence from Airbnb. *Proceedings of the 2018 ACM Conference on Economics and Computation*, 5–6. https://doi.org/10.2139/ssrn.3006832

Barron, K., Kung, E., & Proserpio, D. (2020). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science, 39*(1), 58-71.

Barros, C. P. (2005). Measuring efficiency in the hotel sector. *Annals of Tourism Research, 32*(2), 456-477. https://doi.org/10.1016/j.annals.2004.07.011

Barros, C. P., & Dieke, P. U. C. (2008). Measuring the economic efficiency of hotels in Portugal. *International Journal of Hospitality Management, 27*(3), 398-408. https://doi.org/10.1016/j.ijhm.2007.07.017

Botsman, R., & Rogers, R. (2010). *What's mine is yours: The rise of collaborative consumption*. HarperCollins.

Boxall, K., Nyanjom, J., & Slaven, J. (2018). Disability, hospitality, and the new sharing economy. *International Journal of Contemporary Hospitality Management, 30*(1), 539-556.

Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *The American Economic Review, 18*(1), 139-165.

Cohen, B., & Kietzmann, J. (2014). Ride on! Mobility business models for the sharing economy. *Organization & Environment, 27*(3), 279-296. https://doi.org/10.1177/1086026614546199

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Cooper, W. W., Seiford, L. M., & Tone, K. (2000). *Data envelopment analysis: A comprehensive text with models, applications, references, and DEA-solver software*. Kluwer Academic Publishers.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2004). *Handbook on data envelopment analysis*. Kluwer Academic Publishers.

Dogru, T., Mody, M., & Suess, C. (2019). Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets. *Tourism Management, 72*, 27-38. https://doi.org/10.1016/j.tourman.2018.11.008

Edelman, B. G., & Geradin, D. (2016). Efficiencies and regulatory shortcuts: How should we regulate companies like Airbnb and Uber? *Stanford Technology Law Review, 19*(2), 293-328.

Edelman, B. G., & Luca, M. (2014). Digital discrimination: The case of Airbnb.com. *Harvard Business School NOM Unit Working Paper, 14-054*.

Espinosa, T. P. (2016). The cost of sharing and the common law: How to address the negative externalities of home-sharing. *Chapman Law Review, 19*(1), 597–627.

Estache, A., de la Fe, B., & Trujillo, L. (2004). Sources of efficiency gains in port reform: A DEA decomposition of a Malmquist TFP index for Mexico. *Utilities Policy, 12*(4), 221-230.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General), 120*(3), 253-290.

Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharmacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis, 3*(1), 85-101.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review, 84*(1), 66-83. https://www.jstor.org/stable/2117971

Frenken, K., & Schor, J. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions, 23*, 3-10. https://doi.org/10.1016/j.eist.2017.01.003

Gansky, L. (2010). *The mesh: Why the future of business is sharing*. Portfolio.

Gössling, S., & Hall, C. M. (2019). Sharing versus collaborative economy: How to align ICT developments and the SDGs in tourism? *Journal of Sustainable Tourism, 27*(1), 74-96. https://doi.org/10.1080/09669582.2018.1560455

Gunter, U., & Önder, I. (2018). Determinants of Airbnb demand in Vienna and their implications for the traditional accommodation industry. *Tourism Economics, 24*(3), 270-293.

Gurran, N., & Phibbs, P. (2017). When tourists move in: How should urban planners respond to Airbnb? *Journal of the American Planning Association, 83*(1), 80-92.

Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism, 18*(12), 1192–1217. https://doi.org/10.1080/13683500.2013.827159.

Guttentag, D. (2017). Regulating innovation in the collaborative economy: An examination of Airbnb's early legal issues. In D. Guttentag & D. Smith (Eds.), *The rise of the sharing economy: Exploring the challenges and opportunities of collaborative consumption*. Nova Science Publishers.

Guttentag, D., Smith, S., Potwarka, L., & Havitz, M. (2017). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research*. https://doi.org/10.1177/0047287517696980

Guttentag, D., Smith, S., Potwarka, L., & Havitz, M. (2018). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research, 57*(3), 342–459. https://doi.org/10.1177/0047287517696980

Hawlitschek, F., Teubner, T., & Gimpel, H. (2016). Understanding the sharing economy: Drivers and impediments for participation in peer-to-peer rental. *Proceedings of the 49th Hawaii International Conference on System Sciences*, 4782-4791.

Horn, K., & Merante, M. (2017). Is home-sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics, 38*, 14-24. https://doi.org/10.1016/j.jhe.2017.08.002

Leibenstein, H. (1966). Allocative efficiency vs. "X-efficiency." *American Economic Review, 56*(3), 392-415.

Liang, L. J., Choi, H. C., & Joppe, M. (2017). Understanding repurchase intention of Airbnb consumers: Perceived authenticity, electronic word-of-mouth, and price sensitivity. *Journal of Travel & Tourism Marketing, 34*(1), 73-89.

Mauri, A. G., Minazzi, R., Nieto-García, M., & Viglia, G. (2018). Humanize your business: The role of personal reputation in the sharing economy. *International Journal of Hospitality Management, 73*, 36-43.

Miller, S. R. (2014). Transferable sharing rights: A theoretical model for regulating Airbnb and the short-term rental market. *SSRN*. https://doi.org/10.2139/ssrn.2514178

Morey, R. C., & Dittman, D. A. (1995). Evaluating a hotel GM's performance: A case study in benchmarking. *Cornell Hotel and Restaurant Administration Quarterly, 36*(5), 30-35.

Möhlmann, M. (2015). Collaborative consumption: Determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behaviour, 14*(3), 193-207.

Oskam, J., & Boswijk, A. (2016). Airbnb: The future of networked hospitality businesses. *Journal of Tourism Futures, 2*(1), 22-42.

Paulauskaite, D., Powell, R., Coca-Stefaniak, J. A., & Morrison, A. M. (2017). Living like a local: Authentic tourism experiences and the sharing economy. *International Journal of Tourism Research, 19*(6), 619-628.

Poon, K. Y., & Huang, W. J. (2017). Past experience, traveler personality, and tripographics on intention to use Airbnb. *International Journal of Contemporary Hospitality Management, 29*(9), 2425-2443.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. Free Press.

Quattrone, G., Proserpio, D., Quercia, D., Capra, L., & Musolesi, M. (2016). Who benefits from the "sharing" economy of Airbnb? *Proceedings of the 25th International Conference on World Wide Web*, 1385–1394. https://doi.org/10.1145/2872427.2874815

Ray, S. C. (1997). *Data envelopment analysis: Theory and techniques for economics and operations research*. Cambridge University Press.

Ray, S. C., & Desli, E. (1997). Productivity growth, technical progress, and efficiency change in industrialized countries: Comment. *The American Economic Review, 87*(5), 1033-1039.

Sthapit, E., & Jiménez-Barreto, J. (2018a). Sharing in the host–guest relationship: Perspectives on the Airbnb hospitality experience. *Anatolia, 29*(2), 282-284.

So, K. K. F., Oh, H., & Min, S. (2018). Motivations and constraints of Airbnb consumers: Findings from a mixed-methods approach. *Tourism Management, 67*, 224-236.

Sundararajan, A. (2016). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. MIT Press.

Thanassoulis, E. (2001). *Introduction to the theory and application of data envelopment analysis: A foundation text with integrated software*. Kluwer Academic Publishers.

Tussyadiah, I. P., & Pesonen, J. (2016). Impacts of peer-to-peer accommodation use on travel patterns. *Journal of Travel Research, 55*(8), 1022-1040. https://doi.org/10.1177/0047287515608505

Volgger, M., Pforr, C., Stawinoga, A. E., Taplin, R., & Matthews, S. (2018). Who adopts the Airbnb innovation? An analysis of international visitors to Western Australia. *Tourism Recreation Research, 43*(3), 305-320.

Wachsmuth, D., & Weisler, A. (2018). Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A: Economy and Space, 50*(6), 1147-1170.

Wieditz, T. (2017). Squeezed out: Airbnb's commercialization of home-sharing in Toronto. *FAIRBNB.CA Coalition*. Retrieved from http://fairbnb.ca/wp-content/uploads/2017/09/Fairbnb_Report_Feb_29.pdf

Xie, K. L., & Mao, Z. (2017). The impacts of quality and quantity attributes of Airbnb hosts on listing performance. *International Journal of Hospitality Management, 67*, 224-233.

Yannopoulou, N., Moufahim, M., & Bian, X. (2013). User-generated brands and social media: Couchsurfing and Airbnb. *Contemporary Management Research, 9*(1), 85-90.

Yang, S. B., Lee, H., Lee, K., & Koo, C. (2018). The application of Aristotle's rhetorical theory to the sharing economy: An empirical study of Airbnb. *Journal of Travel and Tourism Marketing, 35*(7), 938-957.

Zekan, B., Onder, I., & Gunter, U. (2019). Benchmarking of Airbnb listings: How competitive is the sharing economy sector of European cities? *Tourism Economics, 25*(7), 1029-1046.

Zekan, B., & Gunter, U. (2021). Zooming into Airbnb listings of European cities: Further investigation of the sector's competitiveness. *Tourism Economics*, 1-23.

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research, 54*(5), 687-705. https://doi.org/10.1509/jmr.15.0204