Analysis of the Impact of Exogenous Variables on the Efficiency of Tourist Accommodation Establishments

Efficiency Analysis on Local Housing in Coastal Portuguese Municipalities

Joana Carreira Domingos

Instituto Superior Técnico, Lisboa, Portugal

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Abstract: Performance evaluation reveals itself as a tool of extreme importance, being one of the most effective ways for an operator to improve its efficiency through the measurement and control of its main production factors and results. In this work, two methodologies were used: Data Envelopment Analysis (DEA) and the Malmquist Productivity Index, which were both run in the software Stata SE. DEA is a benchmarking technique based on mathematical programming and is one of the methods used to perform performance measurement, assessing the relative efficiency of a group of Decision-Making Units (DMUs). The MPI compares the efficiency between two periods, providing information on productivity improvements, since it considers multiple time periods, allowing a comprehensive understanding of efficiency fluctuations. These methodologies were chosen to evaluate a set of 38 coastal municipalities that have local accommodation, over a period of 4 years in Portugal. The model has as inputs the accommodation capacity, the number of rooms, and the number of dwellings, and, as outputs, total revenue, number of guests, and number of nights spent. The main conclusions point to a high inefficiency in a significant number of municipalities when considering their local housing. The Malmquist index revealed a decrease in average annual productivity due to a decline in technological change but with positive contributions from technical change. The pandemic had a significant impact on the results. A systematic methodology for ranking municipalities based on efficiency was developed, with Sintra ranking first. Viana do Castelo and Castro Marim also performed well in terms of efficiency.

Keywords: Tourism, Portuguese Municipalities, Tourist Accommodations, DEA, Malmquist Index, Efficiency Analysis

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1. Introduction

1.1. Context and Motivation

Travel has transformed from a necessity to a leisure pursuit, primarily enjoyed by the affluent, throughout history, emerging as a substantial economic contributor, generating employment opportunities, and influencing the GDP, with accommodation establishments playing a crucial role in the tourism industry by directly influencing tourists' satisfaction and experiences (Jayapalan, 2001; Theobald, 2013).

Portugal is a country that heavily relies on tourism for economic growth due to its advantageous location, cultural diversity, and natural attractions (Turismo de Portugal, 2021). However, the COVID-19 pandemic has significantly impacted global tourism, leading to a decline in visitor numbers and revenue, which raised concerns regarding sustainability and resource management within the industry (Turismo de Portugal, 2021; INE, 2021a).

To address these issues, this thesis focuses on evaluating the efficiency of municipalities in Portugal's tourism and accommodation sector. By utilizing methodologies like DEA and the MPI, the research aims to estimate efficiency levels and provide valuable insights into resource allocation and sustainability practices in local housing throughout a set of coastal Portuguese municipalities.

1.2. Objectives

This research aims to analyze and assess the efficiency levels of municipalities with local accommodation over a specific period. The primary objective is to provide quantitative insights into the accommodation sector, contributing to a better understanding of the efficiency of municipalities and aiding in their evaluation and improvement. The specific objectives of this dissertation are as follows:

1. To comprehensively understand Portuguese coastal tourism, which is considered a valuable asset for Portugal.
2. To employ specific methodological approaches to evaluate the performance of Portuguese municipalities in their tourism sector. Each municipality's tourist accommodation is treated as a market to assess efficiency.
3. To examine variations in efficiency values based on chosen methodologies, variables, and year-to-year changes within a specific period. The aim is to gain insights into the fluctuation of efficiency levels and understand the factors influencing these variations.

2. Tourism

2.1. History

Travel has played a crucial role throughout human history, serving various purposes, and evolving from a necessity to a leisure activity (Lickorish & Jenkins, 2007). The concept of tourism emerged with the rise of the middle class, and the advancements in transportation and communication, resulting in significant growth and development in the industry (Jayapalan, 2001; Theobald, 2013). From ancient civilizations to modern times, people have traveled for various reasons, including trade, education, religion, and exploration (Jayapalan, 2001).

The advent of the internet and social media has revolutionized how people plan and experience their travels, providing greater convenience and accessibility (Zeng & Gerritsen, 2014). Tourism is now considered the largest industry in the world, with substantial contributions to GDP and employment (Theobald, 2013). Sustainable tourism practices are increasingly recognized as essential for balancing economic development with environmental preservation and community well-being (Jaini et al., 2012). However, the industry also faces challenges, such as the impact of the COVID-19 pandemic and concerns about sustainability and resource management.

Overall, the evolution of travel and tourism reflects the changing needs, desires, and opportunities of societies. Understanding its history and current trends is crucial for effectively managing the industry, ensuring its sustainability, and maximizing its benefits for individuals, communities, and destinations.

2.2. Definition

Defining tourism is a complex task due to its diverse interpretations among researchers, industry professionals, and governments (Hunt & Layne, 1991; Tribe, 1997). The lack of consensus on definitions can undermine the credibility of tourist data and difficult the understanding of its economic impact (Yu et al., 2012). However, clear definitions are crucial for research, statistics, regulation, and industry development (Panosso Netto, 2009).

Tourism is considered a multidisciplinary field that incorporates economics, sociology, culture, and geography (Theobald, 2013). It encompasses various industries, enterprises, resources, and attractions, making it a dynamic and diverse sector (Kaiser and Helber, 1978:4-5 in Leiper, 1979). Different dimensions such as trip goal, distance traveled, duration, place of residence, and transportation method contribute to our understanding of tourism (Theobald, 2013).

There are multiple perspectives and categorizations used to define tourism, including economic, technical, and holistic approaches, each providing unique insights (Leiper, 1979).

The academic study of tourism has led to the development of a body of knowledge, while education and training aim to equip individuals with industry-specific skills. Categorizing tourism into domestic, inbound, and outbound types further refines its classification (Lickorish & Jenkins, 2007).

Defining tourism emphasizes temporary movement and staying away from one's usual place of residence for recreation, business, education, or health purposes (Gonap, 2018). The presence of an overnight stay and voluntary use of time and financial resources differentiate tourists from day trippers (Leiper, 1979).

The study of tourism is vital for acquiring knowledge and diverse perspectives, although research coverage is still limited, and there may be undiscovered aspects within the industry. Establishing clear definitions and boundaries is essential to enhance understanding and facilitate exploration in tourism research and practice (Tribe, 1997).

2.3. Accommodation Industry

Europe is a popular tourist destination with a rich cultural history and major attractions. The European Union (EU) member countries receive a significant number of international tourists, and the tourism industry in Europe has played a substantial role in GDP, job creation, and balance of payments (UNWTO, 2018).

Within the EU, various types of accommodation facilities are available, including hotels, vacation rentals, and camping sites, which are crucial for shaping tourists' satisfaction and perception (Viskers and Znotina, 2017; UNWTO, 2018). Portugal heavily relies on tourism for income and employment, with a significant share of its GDP coming from the sector (Proença and Soukiazis, 2005).

The COVID-19 pandemic had a significant impact on the tourism industry, leading to a decline in visitor numbers compared to pre-pandemic levels. However, there has been a gradual recovery, though not yet reaching pre-pandemic levels. Recently, Portugal's tourist accommodation industry has witnessed an increase in visitors, overnight stays, and overall income compared to the previous year, which can be seen in Figure 1 (Turismo de Portugal, 2021).

Figure 1 - Number of International Arrivals and Overnight Stays (Statista, April 6 2023)

3. State-of-the-Art

3.1. Efficiency

Efficiency, similar to tourism, has context-dependent definitions. It involves achieving maximum output with minimal inputs and reducing waste. Efficiency encompasses various resources such as time, money, human capital, equipment, and energy (Banton, 2022). The definition and measurement of efficiency vary across contexts.

Farrell (1957) and Charnes et al. (1978) introduced the concept of efficiency as the scaling required to transform observations from an inefficient unit to an efficient production function. Efficiency is often associated with doing things correctly, while effectiveness focuses on doing the right things. Effectiveness measures goal achievement and is essential for evaluating business performance relative to strategic objectives (Asmild, 2007).

Efficiency can be categorized into technical and allocative efficiency. Technical efficiency aims to maximize outcomes using the fewest inputs possible. Allocative efficiency focuses on the optimal input combination that minimizes production costs and considers health outcome distribution in the community (Farrell, 1957; Palmer & Torgerson, 1999).

3.2. Performance Evaluation Methodologies

Performance evaluation methodologies can be categorized into parametric and non-parametric approaches, as identified by Marques (2011). These methodologies can further be classified into two categories based on whether they utilize reference frontiers or not. Non-parametric procedures do not require parameter inference from a sample, while parametric ones do. These approaches can also be divided into stochastic or deterministic methodologies based on whether they consider random error or not, as well as efficient frontier or average adjustments.

Performance evaluation methodologies aim to assess the efficiency of DMUs compared to a frontier. Two main methods for constructing an efficient frontier are parametric and non-parametric approaches. Parametric methods, like linear regression and stochastic frontier analysis (SFA), estimate the production frontier using function estimation. Non-parametric methods, such as data envelopment analysis (DEA), construct the frontier based on empirical observations (Drake & Simper, 2005). Efficiency classification is determined by comparing with best practices or average adjustment (Marques & Silva, 2006).

Both approaches involve defining the goal and estimating the efficient frontier. Non-parametric methods like DEA use linear programming techniques without assumptions, while parametric methods like SFA estimate the frontier function using statistical data and parameters (Drake & Simper, 2005). DEA is advantageous for evaluating efficiency in tourism services with multiple outputs, while SFA is limited to one output. DEA is often preferred for assessing non-profit institutions, while SFA allows for statistical hypothesis testing (Coeli et al., 2005).

Considering the differences between DEA and SFA and the nature of the study in the tourism industry, the non-parametric DEA approach is chosen.

DEA is a non-parametric methodology used to evaluate the efficiency of DMUs that have multiple inputs and outputs offering valuable insights into efficiency and it serves as a tool for benchmarking performance. It seeks to determine the optimal output-to-input ratio for each DMU while considering the performance of other units (Charnes et al., 1978). DEA models can be categorized based on input or output orientation, as well as Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) models. The specific choice of DEA models depends on the specific requirements and characteristics of the study at hand (Charnes et al., 1978; Banker et al., 1984).

However, DEA has certain limitations, including a higher likelihood of considering more DMUs as efficient as the number of variables increases, challenges in formulating statistical hypotheses, and the inability to measure "absolute" efficiency. DEA focuses on relative efficiency and assumes that DMUs not on the efficiency frontier are inefficient. Hypothesis testing is not applicable within the DEA framework (Dyson et al., 2002; Sarafidis, 2002).

For DEA to be applied, the studied organizations should be homogeneous, with comparable objectives and similar tasks in similar external environments. The variables, including inputs and outputs, must be consistent across all DMUs, with variations only in their magnitudes (Thanassoulis, 2001).

3.3. Malmquist Productivity Index (MPI)

The MPI was introduced by Malmquist in 1953. It compares the VRS efficiency of a second period to that of a first period, measuring changes in efficiency over time and enabling comparisons between different periods.

The MPI is a useful tool for evaluating productivity improvements over time and comparing efficiency values across different time periods for specific DMUs, which goes beyond the static efficiency levels provided by DEA. Relying on data from a single year may lead to biased conclusions due to the omission of market dynamics. Examining efficiency fluctuations over multiple periods is crucial since DMUs can vary in efficiency over different time frames (Caves et al., 1982; Chen & Ali, 2004)

The MPI is particularly effective for analyzing total factor productivity changes. It can be broken down into components that represent technical change (TECH) and technological change (TECCH). An MPI greater than 1 indicates improved performance between two periods, while an MPI of 1 suggests no change, and an MPI smaller than 1 signifies a decline in performance (Färe et al., 1994)

3.4. Literature Review

Efficient management of inputs is identified as a crucial factor in the success of tourist destinations by Cracolici et al. (2008). The competitiveness of hotels is highlighted by Corne (2015) as a critical element in attracting tourists and enhancing overall tourism efficiency. Thus, evaluating the efficiency of the hospitality sector becomes essential in assessing the efficiency of the entire tourism industry. To gain comprehensive insights into these concepts and their application in the tourism context, an extensive literature review was conducted to identify the most relevant articles for the dissertation.

Agabo-Mateos et al. (2014) assessed the efficiency and production changes of Andalusian Public Chain of Youth Hostels (AYH) from 2003 to 2012 using non-parametric DEA and Malmquist indices. The results showed AYH had higher technical efficiency levels compared to the Spanish hotel industry, but productivity declined during the economic recession.

Benito et al. (2014) analyzed the performance of 17 Spanish Autonomous Communities (ACs) from 2002-2010 using DEA and identified inefficiencies and a slow decline in technical efficiency levels during the economic recession.

Detotto et al. (2014) studied Italy's hospitality industry, focusing on hotels and restaurants, at the regional level from 2000 to 2004. They found significant regional inefficiencies and identified variables such as the underuse of infrastructure and excessive seasonal fluctuations as causes of economic inefficiency.

Pereira Oliveira et al. (2015) evaluated the productivity levels of 28 4 and 5-star accommodations in Portugal's Algarve region from 2005 to 2007. They identified high levels of inefficiency and factors such as management, inadequate use of infrastructure, seasonality, and the institutional and contextual environment as affecting efficiency differences.

Ohe and Peypoch (2016) studied ryokans in the Japanese tourist industry using the WDEA method. They found larger ryokans to be more effective and recommended closing the efficiency gap between various facility sizes.

Solana-Ibáñez et al. (2016) analyzed the efficiency and productivity change in the Spanish tourism sector from 2005 to 2013. They identified significant tourist attractions and emphasized the importance of responsible tourism and competitive interdependence among all actors in destinations.

Oukil et al. (2016) evaluated the effectiveness of hotels in Oman using a two-stage DEA approach. They found most hotels to be technically inefficient and identified star ratings and cultural attractions as significant factors in determining efficiency.

Guccio et al. (2017) investigated the relationship between cultural participation and tourism destination performance in Italian regions from 2004 to 2010. They found that cultural participation had a positive effect on tourism efficiency and recommended coordination between policies to enhance effectiveness.

Soysal-Kurt (2017) examined the efficiency of the tourist industries in 29 European nations and identified both efficient and inefficient nations. The study provided suggestions for boosting productivity in nations with low efficiency.

Oukil and Al-Zidi (2018) studied the effectiveness of the hotel sector in Oman and identified factors affecting operational efficiency. They recommended decentralized investment policies and further research using expanded DEA models.

Niavis and Tsiotas (2019) evaluated the efficiency and effectiveness of Mediterranean coastal resorts' tourist performance. They found improper management to be the main cause of inefficiency and suggested interventions to enhance areas' relative position in terms of efficacy and efficiency.

Rodríguez et al. (2021) analyzed the efficiency of hotel supply in the Canary Islands and found potential for improvement in technological efficiency. They identified differences in efficiency based on hotel size, star rating, and location.

Pavković et al. (2021) assessed the efficiency of the tourism industry in various European countries and regions. They identified variations in efficiency levels and emphasized the importance of enhancing efficiency for maximizing economic benefits.

Overall, the studies utilized methods such as DEA, Malmquist indices, and WDEA to evaluate efficiency, productivity, and performance in the tourism industry, providing insights into factors influencing efficiency and offering recommendations for improvement.

4. Case-Study

4.1. Sample and Data Collection

This study focuses on the efficiency analysis of tourist accommodations in specific Portuguese coastal municipalities, particularly local housing (*alojamento local*). The selection of DMUs is an important step, and it is essential to ensure homogeneity among the organizations being studied. In this case, the chosen DMUs are the Portuguese coastal municipalities, totaling 92 municipalities out of a total of 308 in Portugal. However, due to data availability, only 38 municipalities will be studied, representing 41.3% of the Portuguese coast.

Coastal areas are defined based on criteria established by EUROSTAT, either by having a maritime border or having at least 50% of their surface area within a distance of less than 10 km from the sea. The selected municipalities are Caminha, Viana do Castelo, Póvoa de Varzim, Alcobaça, Caldas da Rainha, Lourinhã, Óbidos, Aveiro, Leiria, Marinha Grande, Pombal, Almada, Oeiras, Setúbal, Sintra, Odemira, Santiago do Cacém, Albufeira, Aljezur, Castro Marim, Faro, Lagoa, Lagos, Loulé, Olhão, Portimão, Silves, Tavira, Angra do Heroísmo, Horta, Lajes do Pico, Ponta Delgada, Santa Cruz das Flores, Calheta, Porto Santo, Ribeira Brava, Santa Cruz, and São Vicente.

Data for constructing the DEA model, including inputs and outputs, was obtained from the INE (National Institute of Statistics) database. The data used in the analysis is from the years 2018, 2019, 2020, and 2021, with the number of local housing units in Portugal being 3,534, 3,223, 2,240, and 2,811, respectively.

4.2. Model Specifications

This study utilizes the DEA (Data Envelopment Analysis) technique to evaluate the effectiveness of local housing in selected Portuguese municipalities. The Banker, Charnes, and Cooper (BCC) model, based on VRS technology, is employed for efficiency analysis due to its simplicity in interpreting results using Stata SE software.

Both input and output orientations are included in the DEA model to comprehensively assess each municipality in the sample. This approach allows for a thorough examination of whether a municipality is more efficient in utilizing inputs to achieve desired outputs or in generating outputs considering the level of inputs. Considering the context of accommodation and tourism, which can be viewed as either public services or profit-driven entities, it is important to consider both perspectives.

The selection of variables for comparing the efficiency levels of municipalities' local housing accommodations is based on standard practices in efficiency analysis within the tourism industry. These variables were chosen based on a literature review and data availability from the INE database. Variables were selected considering their relevance and the availability of data for the years 2018 to 2021. The chosen inputs and outputs are presented in Table 1.

Table 1 - Inputs and Outputs of the Model

Inputs	Outputs
Accommodation Capacity	Total Revenue (€ in thousands)
Number of Accommodations	Number of Guests
Number of Bedrooms	Number of Nights Spent

5. Results

5.1. Input-Oriented Model

Table 2 presents the statistical parameters of the data related to the efficiency of municipalities.

Table 2 - Statistical Parameters Input-Oriented Model

	Efficiency Measures		
	CRS	VRS	Scale
Mean	64,6%	73,6%	88,3%
Standard Deviation	21,8%	22,0%	15,0%
Minimum	25,2%	26,6%	30,4%
Efficient Municipalities	20	42	20
Number of DMUs	152	152	152

Some conclusions regarding the results are stated:

- In terms of CRS efficiency, out of the 152 DMUs analyzed, only 20 were considered efficient, indicating that approximately 86.8% of the sample was inefficient, with an average efficiency score of 64.6%.
- VRS efficiency identified 42 efficient DMUs, meaning that around 72.4% of all DMUs were inefficient, with an average efficiency score of 73.6%.
- Scale efficiency also found 20 efficient DMUs, with approximately 86.8% of the DMUs being inefficient, but with an average efficiency score of 88.3%.

Sintra was the only municipality consistently efficient in all four years analyzed. Several other municipalities, including Viana do Castelo, Óbidos, Marinha Grande, Pombal, Oeiras, Castro Marim, Faro, Portimão, and Santa Cruz, achieved 100% efficiency in certain years.

For VRS efficiency, as stated, 42 DMUs were considered efficient, with Pombal, Sintra, and Santa Cruz das Flores consistently achieving maximum efficiency.

Regarding returns to scale, among the 152 DMUs, 85 exhibited increasing returns to scale (IRS), 20 had CRS, and 47 demonstrated decreasing returns to scale (DRS). This suggests that 85 DMUs could improve efficiency by increasing input units, while the 47 DMUs with DRS should focus on enhancing their work processes.

Benchmarking analysis using reference sets revealed Sintra as the only DMU consistently used as a peer reference throughout the four years due to its consistent 100% efficiency. Other DMUs, such as Óbidos, Oeiras, and Leiria, were frequently used as peer references in specific years. Some peculiar cases were noted, such as Alcobaça and Olhão having the highest number of peer references in 2020, and certain efficient DMUs not serving as peer references for the inefficient ones. Overall, despite achieving high-efficiency scores, some municipalities still have the potential for improvement based on the presence of peer references.

5.2. Output-Oriented Model

Table 3 presents the statistical parameters.

Table 3 - Statistical Parameters Output-Oriented Model

	Efficiency Measures		
	CRS	VRS	Scale
Mean	64,6%	69,9%	93,1%
Standard Deviation	21,8%	23,4%	9,2%
Minimum	25,2%	26,1%	53,5%
Efficient Municipalities	20	36	22
Number of DMUs	152	152	152

Some conclusions regarding the results are stated:

- In terms of CRS efficiency, out of the 152 DMUs analyzed, only 20 were considered efficient, indicating that approximately 86.8% of the sample was inefficient, with an average efficiency score of 64.6%. Sintra was the only municipality that consistently achieved maximum efficiency throughout the four years.
- VRS efficiency identified 36 efficient DMUs, meaning that around 76,3% of all DMUs were inefficient, with an average efficiency score of 69,9%. Sintra again stood out as the only municipality with 100% efficiency in all years. Other municipalities, such as Viana do Castelo, Óbidos, and Leiria, also achieved 100% efficiency in certain years.
- In terms of scale efficiency, 22 DMUs were considered efficient, with 85.5% of the DMUs assumed to be inefficient. The average scale efficiency score was 93.1%.

The analysis also revealed the variable returns to scale behavior of the DMUs. Among the DMUs analyzed, 90 exhibited increasing returns to scale, indicating that they could enhance their efficiency by increasing the number of output units. 22 DMUs had constant returns to scale, while 40 DMUs demonstrated decreasing returns to scale, suggesting that they could improve their efficiency by using fewer inputs.

The peer reference analysis identified Sintra as the most frequently used DMU as a reference throughout the four years. However, other DMUs, such as Óbidos, Leiria, and Almada, were also frequently used as peer references in certain years. Overall, the findings suggest that while some DMUs achieved maximum efficiency, there is still potential for improvement in various municipalities, as indicated by the presence of peer references even for efficient DMUs.

5.3. Comparison Analysis

The VRS efficiency results depicted in Figure 2 represent average values derived from models produced by each municipality over the years 2018 to 2021. The graph illustrates that the input-oriented model has the highest frequency of findings in the 50%–60%, 80%–90%, and 90%–100% efficiency ranges, totaling eight instances. Conversely, the output-oriented model primarily yields results in the 50%–60% range, amounting to nine instances. Notably, only the input-oriented model recognizes Pombal, Sintra, and Santa Cruz das Flores as technically efficient, while the output-oriented model solely acknowledges Sintra's technical efficiency. The average VRS efficiency of the output-oriented model is lower at 69.9%, in contrast to the input-oriented model's average VRS efficiency of 73.6%.

Figure 3 presents the average CRS efficiencies of each municipality. The input-oriented model demonstrates the highest frequency of results in the 50%-60% and 60%-70% ranges, with eight municipalities falling into each category. In contrast, the output-oriented model primarily yields results (nine municipalities) in the 50%-60% range. Comparing Figures 7 and 8, it is evident that CRS efficiencies exhibit a broader distribution across various ranges of results.

Sintra stands out as the only municipality deemed efficient in both models throughout the analyzed years. The average CRS efficiency for both models is 64.6%.

Figure 4 presents the percentages of scaling behavior. In the input-oriented model, approximately 55.9% of DMUs exhibit increasing returns to scale (IRS), while the output-oriented model shows 59.2% of DMUs displaying this behavior. For constant returns to scale (CRS), 13.2% and 14.5% of DMUs demonstrate this pattern in the input and output-oriented models, respectively. Regarding decreasing returns to scale (DRS), the input-oriented model has 30.9% of DMUs exhibiting this behavior, whereas the output-oriented model has 26.3%.

The benchmark sets in the output-oriented model exhibit less diversity compared to those in the input-oriented model, mainly due to the presence of fewer technically efficient DMUs in the output-oriented model. As seen in Figure 5, the input-oriented model presents, not only a higher number of peer references but also a larger sample of the municipalities that serve as said references, when compared to the output-oriented model.

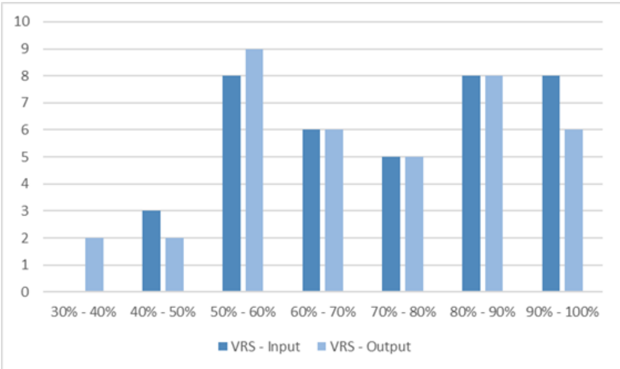

Figure 2 - Results of the VRS Efficiency Between the Two Models

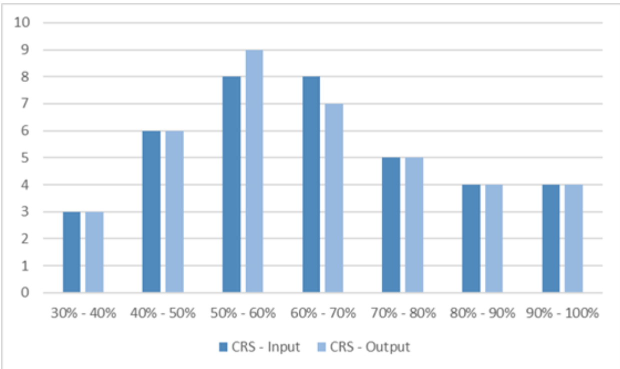

Figure 3 - Results of the CRS Efficiency Between the Two Models

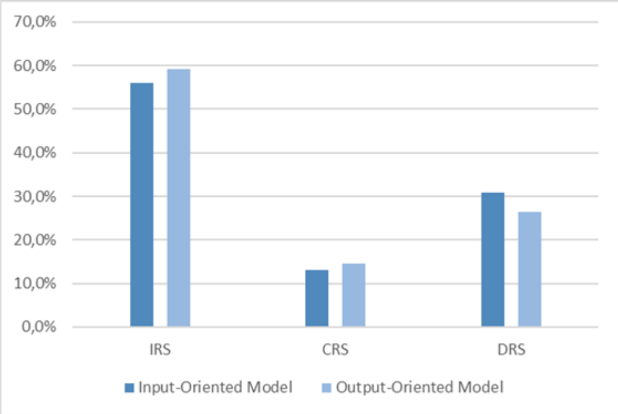

Figure 4 - Results of the Scaling Behaviour Between the Two Models

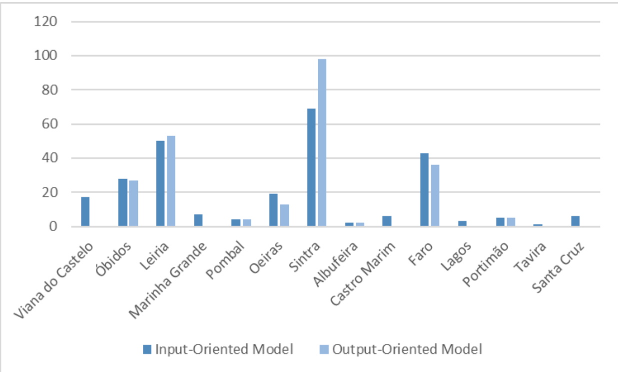

Figure 5 - Results of Peer References Between the Two Models

5.4. Malmquist Productivity Index

The Malmquist index was used to analyze the productivity changes of 38 municipalities over a 4-year period. The results showed that average annual productivity decreased by 1.7%. The overall performance improvement was driven by positive contributions in technical change, leading to a 2.4% efficiency improvement, while efficiency related to technological change declined by 5.3%. The COVID-19 pandemic may have influenced these results, particularly in the last two years.

Out of the 38 municipalities, 22 experienced productivity losses, while 16 showed productivity gains mainly due to improvements in technical change. Only one municipality demonstrated gains in technological change.

Regarding Total Factor Productivity Change (TFPCH), one municipality consistently experienced productivity losses. In terms of technical efficiency (TECH), three municipalities showed losses, while three consistently performed well. For technological change (TECCH), all municipalities had periods of both gains and losses.

From Figure 6, it can be analyzed the average values. There was a decrease in total productivity of 4.4% for the period 2018-2019, primarily attributed to a decline in technical efficiency and technological progress. The 2019-2020 period had a significant decline in total productivity, likely influenced by the pandemic. However, between 2020 and 2021, there was a substantial recovery with notable increases in technical efficiency and technological change. The strong growth in tourism in 2021 resulted in a 36.9% increase in total productivity, indicating a return to normal values.

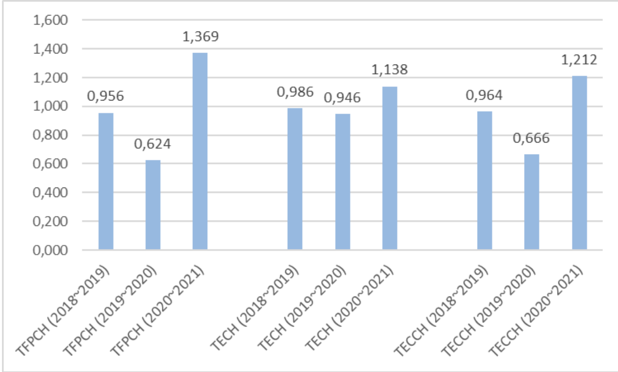

Figure 6 - Mean Values of TFPCH, TECH, and TECCH

When analyzing the overall results, it can be observed that Óbidos had the poorest performance in terms of Total Factor Productivity Change (TFPCH) and Technological Change (TECCH), experiencing significant losses. On the other hand, Horta showed the best performance in TFPCH, indicating a notable gain. Marinha Grande demonstrated the highest improvement in Technical Efficiency (TECH), while Pombal showed the most significant improvement in Technological Change (TECCH).

5.5. Ranking of the Municipalities

This research study aimed to rank municipalities based on their efficiency levels using a methodology inspired by Aristovnik et al. (2013). The ranking method utilized the geometric mean of the VRS efficiencies over multiple years to determine an overall efficiency score for each municipality. Notable findings include Sintra consistently holding the first-place ranking without changes, indicating a consistently high performance, as seen in Table 4. 5 municipalities also achieved top rankings in most years, demonstrating their sustained efficiency, while 6 municipalities maintained relatively stable rankings with minimal changes over the four-year period.

Table 4 - Final Ranking of the Municipalities

DMU	VRS Efficiency	Final Ranking
Sintra	100,0%	1
Viana do Castelo	99,7%	2
Castro Marim	98,3%	3
Faro	94,7%	4
Pombal	92,3%	5
Albufeira	91,3%	6
Tavira	91,2%	7
Oeiras	89,9%	8
Santa Cruz das Flores	87,7%	9
Aveiro	87,4%	10
Leiria	84,5%	11
Lagos	82,9%	12
Loulé	82,4%	13
Portimão	82,2%	14
Ponta Delgada	75,9%	15
Ribeira Brava	75,5%	16
Marinha Grande	75,3%	17
Odemira	71,9%	18
Óbidos	70,5%	19

Table 4 – Final Remarks of the Municipalities (Continuation)

DMU	VRS Efficiency	Final Ranking
Caminha	69,3%	20
Almada	67,9%	21
Lagoa	66,1%	22
Lourinhã	61,5%	23
Aljezur	60,3%	24
Santa Cruz	60,2%	25
Póvoa de Varzim	60,1%	26
São Vicente	59,5%	27
Setubal	57,3%	28
Angra do Heroísmo	54,6%	29
Silves	52,2%	30
Calheta (Madeira)	51,7%	31
Olhão	51,1%	32
Horta	49,6%	33
Santiago do Cacém	46,7%	34
Alcobaça	46,5%	35
Lajes do Pico	45,6%	36
Porto Santo	38,6%	37
Caldas da Rainha	37,4%	38

6. Conclusions

6.1. Summary

This research study focused on evaluating the efficiency of 38 Portuguese coastal municipalities with local housing over a 4-year period. The study employed Data Envelopment Analysis (DEA), a non-parametric method, to assess relative efficiency. Both input and output orientations were used to measure efficiency, considering three inputs (accommodation capacity, number of accommodations, and number of bedrooms) and three outputs (total revenue, number of guests, and number of nights spent) specific to the accommodation sector.

Sintra consistently achieved the highest efficiency ranking throughout the study period, while other municipalities showed varying levels of efficiency. The analysis revealed that most municipalities were considered inefficient, and only a small percentage exhibited high-efficiency levels. Returns to scale analysis indicated that increasing input units could improve efficiency for most municipalities.

The Malmquist index was used to examine productivity changes over time. The overall average annual productivity experienced a decrease primarily due to a decline in technological change, but there were positive contributions from technical change, leading to improved efficiency.

A systematic methodology for ranking municipalities based on efficiency was developed, using the geometric mean of VRS efficiencies across multiple years. Sintra consistently ranked first, and some municipalities consistently performed well, while others maintained stable rankings. The final ranking considered efficiency scores across all years, with Sintra, Viana do Castelo, and Castro Marim being the top three municipalities in terms of overall efficiency.

Overall, this study provides insights into the efficiency and productivity of Portuguese coastal municipalities in the housing sector, highlighting areas for improvement and identifying top-performing municipalities.

6.2. Conclusive Thoughts

This research study evaluated the efficiency of Portuguese coastal municipalities in the housing sector using DEA and provided several conclusive thoughts based on the findings.

The majority of municipalities were found to be inefficient in terms of their housing sector performance, highlighting the need for resource optimization and output improvement. Benchmarking against efficient municipalities like Sintra, Óbidos, and Leiria can guide strategies for enhancing efficiency.

Increasing returns to scale were observed, suggesting the potential benefits of scaling up housing capacity and resource allocation.

The study also identified a decline in overall average annual productivity, mainly due to a decrease in technological change influenced by the COVID-19 pandemic.

A systematic methodology for ranking municipalities based on efficiency was developed, with Sintra consistently ranking first. Other efficient municipalities, such as Viana do Castelo and Castro Marim, were also acknowledged.

The findings emphasize the importance of strategic management interventions, adopting best practices, and adapting to changing technological landscapes. Collaboration and knowledge sharing among municipalities can contribute to sectoral improvement in local housing.

6.3. Limitations

It is important to acknowledge the limitations of this research to prevent misinterpretations and ensure accurate conclusions. The limitations include a lack of restating the research objective in the title, the dependence of efficiency values on specific variables chosen for the DEA model, a limited sample size of 38 coastal municipalities, potential data gaps in local housing representation, a lack of super-efficiency analysis and outlier handling, the impact of the pandemic on the tourism and hospitality sectors during the study period, and the relative nature of DEA efficiency assessment. These limitations highlight the need for further research, consideration of additional variables, and a focus on continuous improvement for efficient municipalities.

6.4. Future Work

This research work holds significance in evaluating the performance of tourist accommodation in Portuguese coastal municipalities from 2018 to 2021. It contributes to the existing literature by focusing specifically on local accommodation in this context and analyzing performance trends over a four-year period. However, further research is recommended to enhance the reliability of the results.

Alternative methodologies such as stochastic frontier models could provide different perspectives, while studies employing DEA and order-m methods could explore the impact of external variables. Additionally, expanding the analysis to include more input and output variables would offer additional insights. Addressing outliers through a future efficiency analysis would also help understand their influence on the overall assessment. Conducting these additional studies would strengthen the findings and contribute to a deeper understanding of the performance evaluation of tourist accommodation.

References

INE (2021a). Tourism Statistics 2021: recovery of tourist activity, but still below 2019 levels. https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_destaques&DESTAQUESdest_boui=540879352&DESTAQUESmodo=2

Jayapalan, N. (2001). Introduction To Tourism, Atlantic Publishers & Distributors.

Theobald, W. F. (2013). Global Tourism. In Global Tourism. Routledge. https://doi.org/10.4324/9780080507446

Turismo de Portugal (2021). Overview – Tourism in Portugal. https://www.turismodeportugal.pt/en/Turismo_Portugal/visao_geral/Pages/default.aspx

Lickorish, L. J., & Jenkins, C. L. (2007). Introduction to Tourism. In Introduction to Tourism. Routledge. https://doi.org/10.4324/9780080495866

Gonap, E. G. (2018) Introduction to Tourism. LAP LAMBERT Academic Publishing.

Zeng, B., & Gerritsen, R. (2014, April). What do we know about social media in tourism? A review. Tourism Management Perspectives. https://doi.org/10.1016/j.tmp.2014.01.001

Hunt, J. D., & Layne, D. (1991). Evolution Of Travel And Tourism Terminology And Definitions. Journal of Travel Research, 29(4), 7–11. https://doi.org/10.1177/004728759102900402

Tribe, J. (1997). The indiscipline of tourism. Annals of Tourism Research, 24(3), 638–657. https://doi.org/10.1016/s0160-7383(97)00020-0

Yu, X., Kim, N., Chen, C. C., & Schwartz, Z. (2012). Are you a tourist? Tourism definition from the tourist perspective. Tourism Analysis, 17(4), 445–457. https://doi.org/10.3727/108354212X13473157390687

Panosso Netto, A. (2009). What is Tourism? Definitions, Theoretical Phases and Principles. Philosophical Issues in Tourism, 43–62.

Leiper, N. (1979). The framework of tourism. Towards a definition of tourism, tourist, and the tourist industry. Annals of Tourism Research, 6(4), 390–407. https://doi.org/10.1016/0160-7383(79)90003-3

Viskers, E., & Znotina, D. (2017). ASSESSMENT OF OPPORTUNITIES FOR DEVELOPMENT OF ACOMMODATION SERVICES IN REZEKNE CITY. Latgale National Economy Research, 1(9), 130. https://doi.org/10.17770/lner2017vol1.9.2652

UNWTO (2018). UNWTO Tourism Highlights 2018 Edition. https://www.e-unwto.org/doi/pdf/10.18111/9789284419876

Proença, S., & Soukiazis, E. (2005). Demand for tourism in Portugal: A panel data approach. Discussion Paper, Nº 29. Escola Superior Agrária, Instituto Politécnico de Coimbra.

Statista. (2023, April 6). Number of international tourists' arrivals and overnight stays in Portugal from 2015 to 2022. https://www.statista.com/statistics/398360/number-of-international-visitors-and-overnight-stays-in-portugal/

Banton, C. (2022, June 2). Efficiency: What It Means in Economics, the Formula to Measure It. Investopedia. https://www.investopedia.com/terms/e/efficiency.asp#toc-what-is-efficiency

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Farrell, M. J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society. Series A (General), 120(3). https://doi.org/10.2307/2343100

Asmild, M., Paradi, J. C., Reese, D. N., & Tam, F. (2007). Measuring overall efficiency and effectiveness using DEA. European Journal of Operational Research, 178(1), 305–321. https://doi.org/10.1016/j.ejor.2006.01.014

Palmer, S., & Torgerson, D. J. (1999). Definitions of efficiency. BMJ, 318(7191), 1136. https://doi.org/10.1136/bmj.318.7191.1136

Marques, R., (2011). Advanced Operations Research: performance evaluation. Slides das aulas de complementos de Investigação Operacional, Instituto Superior Técnico.

Drake, L. M., & Simper, R. (2005). Police efficiency in offences cleared: An analysis of english "Basic Command Units." International Review of Law and Economics, 25(2). https://doi.org/10.1016/j.irle.2005.06.003

Marques, R., & Silva, D. (2006). Inferência estatística dos estimadores de eficiência obtidos com a técnica fronteira não paramétrica de DEA: Uma metodologia de Bootstrap. Associação Portuguesa de Investigação Operacional, 26(1). http://apdio.pt/documents/10180/15548/n5.pdf

Coelli, T. J., Prasada Rao, D. S., O'Donnell, C. J., & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. In An Introduction to Efficiency and Productivity Analysis. Springer US. https://doi.org/10.1007/b136381

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. https://doi.org/10.1287/mnsc.30.9.1078

Dyson, A., Howes, A., & Roberts, B. (2002). A systematic review of the effectiveness of school-level actions for promoting participation by all students. EPPI-Centre, Social Science Research Unit, Institute of Education.

Sarafidis, V. (2002). An Assessment of Comparative Efficiency Measurement Techniques. Europe Economics, 1–21. https://www.semanticscholar.org/paper/An-Assessment-of-Comparative-Efficiency-Measuremen/c6f7f16ec511e8d4143c73d3a521398aa3331d2c

Thanassoulis, E. (2001). Introduction to the Theory and Application of Data Envelopment Analysis. In Introduction to the Theory and Application of Data Envelopment Analysis. Springer US. https://doi.org/10.1007/978-1-4615-1407-7

Malmquist, S. (1953). Index numbers and indifference surfaces. Trabajos de Estadistica, 4(2), 209–242. https://doi.org/10.1007/BF03006863

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. Econometrica, 50(6), 1393. https://doi.org/10.2307/1913388

Chen, Y., & Ali, A. I. (2004). DEA Malmquist productivity measure: New insights with an application to computer industry. European Journal of Operational Research, 159(1), 239–249. https://doi.org/10.1016/S0377-2217(03)00406-5

Färe, R., Grosskopf, S., & Lovell C. (1994). Production Frontiers. New York: Cambridge University Press.

Cracolici, M. F., Nijkamp, P., & Rietveld, P. (2008). Assessment of tourism competitiveness by analysing destination efficiency. Tourism Economics, 14(2), 325–342. https://doi.org/10.5367/000000008784460427

Corne, A. (2015). Benchmarking and tourism efficiency in France. Tourism Management, 51, 91–95. https://doi.org/10.1016/j.tourman.2015.05.006

Aristovnik, A., Seljak, J., & Mencinger, J. (2013). Relative efficiency of police directorates in Slovenia: A non-parametric analysis. Expert Systems with Applications, 40(2), 820–827. https://doi.org/10.1016/j.eswa.2012.08.027

Agabo-Mateos, F. L., Escobar Pérez, B., & Lobo Gallardo, A. (2014). Measuring efficiency of the youth hostel sector in Andalusia using an adapted dea model. Cultura, desarrollo y nuevas tecnologías: VII Jornadas de Investigación en Turismo, Sevilla, 11 y 12 de Junio de 2014 (pp. 185–210). Retrieved from http://dialnet.unirioja.es/servlet/extart?codigo=4769522

Benito, B., Solana, J., & López, P. (2014). Determinants of Spanish regions' tourism performance: A two-stage, double-bootstrap data envelopment analysis. Tourism Economics, 20(5), 987–1012. https://doi.org/10.5367/te.2013.0327

Detotto, C., Pulina, M., & Brida, J. G. (2014). Assessing the productivity of the italian hospitality sector: A post-WDEA pooled-truncated and spatial analysis. Journal of Productivity Analysis, 42(2), 103–121. https://doi.org/10.1007/s11123-013-0371-x

Pereira Oliveira, R. S. L., Craveiro Pedro, M. I., & da Cunha Marques, R. D. R. (2015). Avaliação da eficiência das empresas hoteleiras do algarve pela metodologia análise de envoltória de dados (DEA). Revista Brasileira de Gestao de Negocios, 17(54), 788–805. https://doi.org/10.7819/rbgn.v17i54.1375

Ohe, Y., & Peypoch, N. (2016). Efficiency analysis of Japanese Ryokans: A window DEA approach. Tourism Economics, 22(6), 1261–1273. https://doi.org/10.1177/1354816616670505

Solana-Ibáñez, J., Caravaca-Garratón, M., & Para-González, L. (2016). Two-stage data envelopment analysis of Spanish regions: Efficiency determinants and stability analysis. Contemporary Economics, 10(3Special Issue), 259–274. https://doi.org/10.5709/ce.1897-9254.214

Oukil, A., Channouf, N., & Al-Zaidi, A. (2016). Performance evaluation of the hotel industry in an emerging tourism destination: The case of Oman. Journal of Hospitality and Tourism Management, 29, 60–68. https://doi.org/10.1016/j.jhtm.2016.05.003

Guccio, C., Lisi, D., Martorana, M., & Mignosa, A. (2017). On the role of cultural participation in tourism destination performance: an assessment using robust conditional efficiency approach. Journal of Cultural Economics, 41(2), 129–154. https://doi.org/10.1007/s10824-017-9295-z

Soysal-Kurt, H. (2017). Measuring Tourism Efficiency of European Countries by Using Data Envelopment Analysis. European Scientific Journal, ESJ, 13(10), 31. https://doi.org/10.19044/esj.2017.v13n10p31

Oukil, A., & Al-Zidi, A. (2018). Benchmarking the Hotel Industry in Oman Through a Three-Stage DEA-Based Procedure. Journal of Arts and Social Sciences [JASS], 9(2), 5. https://doi.org/10.24200/jass.vol9iss2pp5-23

Niavis, S., & Tsiotas, D. (2019). Assessing the tourism performance of the Mediterranean coastal destinations: A combined efficiency and effectiveness approach. Journal of Destination Marketing and Management, 14. https://doi.org/10.1016/j.jdmm.2019.100379

Rodríguez, F. J. L., Lorenzo Alegría, R. M., & Martín Rivero, R. (2021). A study of hotel sector efficiency in the Canary Islands. Journal of Tourism Analysis: Revista de Análisis Turístico (JTA), 28(1). https://doi.org/10.53596/jta.v28i1.374

Pavković, V., Jević, G., Jević, J., Nguyen, P. T., & Sava, C. (2021). DETERMINING EFFICIENCY OF TOURISM SECTOR IN CERTAIN EUROPEAN COUNTRIES AND REGIONS BY APPLYING DEA ANALYSIS. Journal of Process Management and New Technologies, 9(3–4), 49–61. https://doi.org/10.5937/jpmnt9-34122