TÉCNICO LISBOA

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

Thesis to obtain the Master of Science Degree in

Industrial Engineering and Management

Supervisor (s): Prof. Maria Isabel Craveiro Pedro

Dr. Rodrigo Soares

Examination Committee

Chairperson: Prof. Dr. José Rui De Matos Figueiras

Supervisor: Prof. Dra. Maria Isabel Craveiro Pedro

Member of the Committee: Prof. Dr. Paulo Alexandre Fernandes Varela Simões Caldas

July 2023

Declaration

I declare that this is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Acknowledgments

This dissertation holds great significance, representing the culmination of the most challenging five years of my life. Despite the difficulties, I wouldn't trade these years for anything, as they have shown me my true capabilities, surpassing my own expectations. Therefore, it is essential for me to express my deepest gratitude to the individuals who have supported me throughout this journey.

First and foremost, I am sincerely thankful to my supervisors, Prof. Maria Isabel Craveiro Pedro e Dr. Rodrigo Soares, whose guidance and assistance were indispensable in completing this dissertation. I am grateful for the unwavering support and patience provided.

Above all, I want to express my heartfelt appreciation to my parents, Marta and Nuno. They not only supported but also showered me with love, patience, motivation, and endless perseverance which have been crucial in all aspects of my life. I am also truly grateful to the rest of my family who have always been proud of me.

To my little sister and best friend, Sofia, thank you immensely. I cannot put into words what you mean to me. You have made me the proudest sister imaginable, and I cannot imagine my life without you.

To my boyfriend, João Gil Costa, who has been with me since the beginning of this challenging five-year journey, words cannot express my gratitude. Having you by my side through it all has made this experience even more incredible than I could have ever imagined.

I would be failing if I didn't thank those who accompanied me on this journey. To those who started as colleagues but have become dear friends, thank you. Laura Monteiro, Madalena Lourenço, Matilde Vasconcelos Ferreira, Alexandre Bukovac, José Ferreira, Francisco Fernandes, and all my other close friends from LEGI/MEGI and LETI/METI, thank you.

To my lifelong best friends who have believed in me and supported me when I needed it the most, I cherish each and every one of you with all of my heart. Madalena Sousa, Maria Moura, Maria Mesquita, Catarina Fatela, Joana Marques, and many more, you know who you are.

To all the people mentioned above, thank you for believing in me, even when I struggled to believe in myself. Thank you all for being a part of this journey that will forever be a part of my life.

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: DEA and the Malmquist Index, which were both run in the software Stata SE. Data Envelopment Analysis (DEA) is a benchmarking technique based on mathematical programming and is one of the methods used to assess the relative efficiency of a group of Decision-Making Units (DMUs). The Malmquist Productivity Index (MPI) compares the efficiency of a second period with that of a first period, 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 selected DEA 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 accommodation establishments. 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

Resumo

A avaliação de desempenho revela-se como uma ferramenta de extrema importância, sendo uma das formas mais eficazes de um operador melhorar a sua eficiência através da medição e controlo dos seus principais fatores de produção e resultados.

Neste trabalho, foram utilizadas duas metodologias: DEA e o Índice de Malmquist, ambas executadas no software Stata SE. A *Data Envelopment Analysis* (DEA) é uma técnica de benchmarking baseada em programação matemática e é um dos métodos utilizados para avaliar a eficiência relativa de um grupo de *Decision-Making Units* (DMUs). O Índice de Produtividade de Malmquist (MPI) compara a eficiência de um segundo período com a de um primeiro período, fornecendo informações sobre melhorias de produtividade, uma vez que considera múltiplos períodos, permitindo uma compreensão abrangente das flutuações de eficiência.

Estas metodologias foram escolhidas para avaliar um conjunto de 38 municípios costeiros em Portugal que dispõem de alojamento local, durante um período de 4 anos. O modelo DEA seleccionado tem como inputs a capacidade de alojamento, o número de quartos e o número de alojamentos, e, como outputs, as receitas totais, o número de hóspedes e o número de dormidas.

As principais conclusões apontam para uma elevada ineficiência num número significativo de municípios no que respeita aos seus estabelecimentos de alojamento. O índice de Malmquist revelou uma diminuição da produtividade média anual devido a um declínio da mudança tecnológica, mas com contributos positivos da mudança técnica. A pandemia teve um impacto significativo nos resultados. Foi desenvolvida uma metodologia sistemática de hierarquização dos municípios com base na eficiência, com Sintra em primeiro lugar. Viana do Castelo e Castro Marim registaram igualmente bons resultados em termos de eficiência.

Palavras-chave: Turismo, Municípios Portugueses, Alojamento Turístico, DEA, Índice de Malmquist, Análise de Eficiência

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ACs: Autonomous Communities

AYH: Andalusian Public Chain of Youth Hostels

BCC: Banker, Charnes, and Cooper

CCR: Charnes, Cooper, and Rhodes

COLS: Corrected Ordinary Least Squares

CRS: Constant Returns to Scale

DEA: Data Envelopment Analysis

DFA: Deterministic Frontier Analysis

DRS: Decreasing Returns to Scale

DMU: Decision-Making Units

EU: European Union

FDH: Free Disposal Hull

GDP: Gross Domestic Product

INE: Instituto Nacional de Estatística

IPHH: Inquérito à Permanência de Hóspedes na Hotelaria e outros alojamentos

IPCAMP: Inquérito à Permanência de Campistas em Parques de Campismo

IPCOL: Inquérito à Permanência de Colonos nas Colónias de Férias

MPI: Malmquist Productivity Index

RTS: Returns to Scale

SFA: Stochastic Frontier Analysis

TFPCH: Total Factor Productivity Index

TECH: Technical Change

TECCH: Technological Change

UNWTO: United Nations' World Tourism Organization

VRS: Variable Returns to Scale

WDEA: Windows Data Envelopment Analysis

1. Introduction

1.1. Context and Motivation

Travel has always been an integral part of human history, serving various purposes such as resource acquisition, exploration, and leisure. The concept of tourism emerged due to increased interest in travel, fuelled by advancements in transportation and communication. Over time, travel evolved from a necessity to a leisure activity, predominantly enjoyed by the wealthier segments of society. Ancient civilizations like the Sumerians, Greeks, Romans, and medieval Christians and Muslims played a significant role in shaping travel patterns for trade, education, religion, and discovery, ultimately leading to the development of tourism as an industry (Jayapalan, 2001).

The Industrial Revolution and subsequent transportation advancements, such as railways and commercial airlines, facilitated mass tourism and contributed to its substantial growth. Tourism became a crucial economic contributor, generating employment opportunities and contributing to the GDP of many countries (Jayapalan, 2001, Theobald, 2013). The advent of the internet and social media further revolutionized travel planning and experiences (Zeng & Gerritsen, 2014).

Europe, particularly Portugal, heavily relies on tourism for economic growth and employment due to its favourable location, cultural and geographical diversity, and natural attractions. Portugal has witnessed significant growth in terms of tourist arrivals and revenue. Accommodation plays a vital role in the tourism industry, directly influencing tourists satisfaction and perception of a destination (Turismo de Portugal, 2021). The EU offers a wide range of accommodation options, including hotels, vacation rentals, camping sites, and RV parks, such as Portugal (UNWTO, 2018).

However, the tourism industry faces challenges, especially in the face of the COVID-19 pandemic, which led to a decline in visitor numbers and revenue worldwide. Sustainability, resource management, and the potential negative impacts on local communities and the environment are growing concerns associated with the industry's rapid growth (Turismo de Portugal, 2021; INE, 2021a).

Given the significance of the tourism and accommodation sectors, it is essential to understand their efficiency and performance. Assessing the efficiency of municipalities in these sectors can provide valuable insights for policymakers and industry stakeholders in improving resource allocation, sustainability practices, and overall economic development.

This thesis aims to explore the efficiency of municipalities in the tourism and hotel sector, with a specific focus on Portugal. By employing methodologies such as Data Envelopment

Analysis and the Malmquist Productivity Index, this research seeks to estimate and analyze the efficiency levels of municipalities. The study will also investigate the factors that influence efficiency and identify suitable variables for analysis based on existing literature. The research is motivated by the need for a comprehensive understanding of the tourism industry's efficiency, especially in the context of Portugal's reliance on tourism for economic growth. By examining the efficiency of municipalities and their accommodation facilities, this study can provide valuable insights into optimizing resource allocation.

1.2. Objectives

This research aims to analyze and assess the efficiency levels of municipalities with local accommodation over a specific period. The primary focus is on using the Data Envelopment Analysis (DEA) methodology to measure efficiency, providing valuable quantitative information about the tourism sector as a whole and specifically the hospitality sector.

The objective is to contribute to a better understanding of the efficiency of municipalities in the context of local accommodation, and how they evolve throughout the years, aiding in the evaluation and improvement of the tourism industry.

The specific objectives of this dissertation are the following:

- To provide a comprehensive understanding of Portuguese coastal tourism, which is considered an asset for Portugal;
- To employ specific methodological approaches to evaluate the performance of Portuguese municipalities in terms of their tourism sector, focusing on the efficiency levels of their tourist accommodation. The analysis treats each municipality's tourist accommodation as a market, aiming to assess their efficiency;
- To examine the variations in efficiency values based on the chosen methodologies, variables, and year-to-year changes within a specific period. The goal is to gain insights into how efficiency levels fluctuate and understand the factors influencing these variations.

1.3. Methodology

The research process involved several important steps. Initially, a comprehensive documentary analysis was conducted, examining articles, scientific journals, books, doctoral theses, master's dissertations, and statistical documents related to the topic. This step helped in gathering a wide range of knowledge and insights on tourism and the accomodation sector, both in Europe and specifically in Portugal.

Next, the focus shifted to identifying and defining suitable methodologies for estimating the efficiency of municipalities. The methodologies considered could be either parametric or non-parametric, depending on their appropriateness for the research objectives.

To proceed with the analysis, a homogeneous sample of Decision-Making Units (DMUs) was created. The selection criteria included the type of housing, ensuring that the chosen DMUs represented the target sector accurately.

Considering the existing literature and previous studying research that utilized similar methodologies, the most appropriate variables were identified. Databases were constructed using data obtained from the National Institute of Statistics (INE), with the municipalities serving as the DMUs. The selected Data Envelopment Analysis (DEA) methodology was preferred due to its ability to handle multiple inputs and outputs, making it suitable for this study. Additionally, the Malmquist index was chosen as a statistical analysis tool to examine efficiency changes over time.

The efficiency levels and Malmquist indexes were then estimated using the Stata SE software. The obtained results were carefully analyzed to draw meaningful conclusions about the efficiency of the municipalities in the tourism and hospitality sector.

Overall, this research process encompassed a systematic and rigorous approach, combining literature review, methodology selection, data collection, and analysis to achieve the research objectives and contribute to the understanding of efficiency in the tourism sector.

1.4. Structure of the Dissertation

This project is based on the following structure:

- Chapter 1 provides a contextualization of the problem by describing the tourism sector, including its market structure, institutional organization, and regulatory framework. It also highlights the motivation behind conducting this study, specifies the objectives of the research, outlines the methodology to be employed, and presents the structure of the document.
- Chapter 2 presents a study of the tourism sector. This study elaborates not only on the history of tourism but also on how it is defined, and its growth throughout the years. Furthermore, the accommodation industry is also elaborated, alongside some data regarding the industry in Europe, and, more specifically, in Portugal.
- Chapter 3 begins by introducing different classifications and definitions of efficiency. It then provides an overview of performance evaluation methodologies, categorizing them into parametric and non-parametric approaches, as well as methods with or without recourse to frontier analysis. A detailed description of the Data Envelopment

Analysis (DEA) methodology, including its main models and specifications, is presented. The chapter also includes a brief explanation of the Malmquist index, which will be used in the model. Additionally, a literature review is included, showcasing research studies that have applied the DEA methodology to evaluate tourist accommodation in various countries.

- Chapter 4 of the dissertation focuses on the case study, exploring the various factors involved in the DEA model. Firstly, the chapter discusses the selection of a homogeneous sample of municipalities and a specific type of accommodation establishment. Next, important model specifications are determined, including the orientation (input or output) and the variables to be considered as inputs and outputs in the analysis. These decisions lay the foundation for the subsequent analysis and evaluation conducted in the study.
- Chapter 5 examines the outcomes of the DEA models' execution in Stata SE and the Malmquist Productivity Index. The chapter studies the choice of peer references for both models as well as the variable returns to scale of the decision-making units (DMUs). The outcomes of the study utilizing the Malmquist Index are provided, along with a comparison of the outcomes derived from the two models. This chapter also finishes with the creation of a rating for municipalities' efficiency based on the years looked at in the dissertation.
- Chapter 6 serves as the concluding section of the dissertation, providing a summary of the main findings and conclusions drawn from the research work. It highlights the key insights obtained through the study. Additionally, the chapter acknowledges the limitations faced during the development of this dissertation. These limitations are discussed, providing insights into potential areas for improvement or further investigation in future research.

2. Tourism

The following chapter will explain the background of tourism, being one of the main themes of this dissertation. Initially, in section 2.1., the history of tourism will be presented, explaining the origin of the concept, how it evolved through the years, its importance, and how it is nowadays, including some data from the years when COVID-19 was prominent and how it affected the sector. In section 2.2., an explanation of the various methods used to define “tourism” and “tourist” and their importance is given, alongside numerous definitions that appeared throughout the years. In Section 2.3. presents a study of the accommodation industry in tourism, which is divided into two subsections: in subsection 2.3.1. some data regarding the said industry in Europe is introduced and, in subsection 2.3.2., a few statistics and features of again the accommodation and tourism industries are presented concerning Portugal. Finally, section 2.4. presents the conclusion of this chapter.

2.1. History

Throughout prehistorical, classical, and medieval times until modern days, mankind has always been known for the necessity of traveling. The main causes were the search for food and other kinds of resources, new lands, better conditions, or even the exploration of new places, meaning that the nomadic population’s basic requirements played a significant role in their travels (Jayapalan, 2001; Theobald, 2013).

As stated by Jayapalan (2001), the interest in traveling comes from the fact that it is a “social phenomenon” which developed exponentially due to transport and communication innovations. However, through the years until the 16^{th} century, when the only means of traveling were by walking, riding a horse, or coach (Gonap, 2018), people in more precarious jobs became more and more stagnant, even if traveling due to war, trading, religion, or other purposes continued (Theobald, 2013). The richer started to enjoy traveling as a leisure activity, from where, later, the concept of tourism would be born (Lickorish & Jenkins, 2007).

The influence of traveling in communities can be seen since ancient times, with the Sumerians, Persians, Greeks, Romans, and medieval Christians and Muslims being highlighted for their travels for trading, education, religion, and discovery (Jayapalan, 2001). However, Babylon and Egypt were where the earliest types of leisure travel could be found (Gonap, 2018). According to Leiper (1979), the word "tourism" appeared during the grand tour in the 18th century when English young men were sent to Europe to conclude their education. The term “tour” has as its origins the Latin word “*tornare*” and the Greek word “*tornos*”, which both imply “lathe or circle” or “the movement around a central point or axis” (Leiper, 1979; Theobald, 2013).

The increase of the middle class and affordable transportation due to the Industrial Revolution marked the beginning of mass tourism, with sea and road transport being the most used, and the railway being an important milestone (Jayapalan, 2001; Theobald, 2013). After World War II, commercial airlines and jet aircrafts were developed, indicating a rapid increase in the need for national or international travel. The tourism sector emerged as a significant new industry due to economic and social factors such as the increase in incomes, the rise of package excursions, the availability of recreational time, and the creation and expansion of paid holidays. The travel industry changed to accommodate the needs of increasingly savvy travelers, and the development of new and better communication methods, such as television, helped to promote the growth of tourism (Lickorish & Jenkins, 2007; Theobald, 2013).

Nowadays, with the rise of the internet and social media, the sector and how people plan their travels have changed drastically, due to various platforms, websites, and applications available to make every process easier for the consumer (Zeng & Gerritsen, 2014). With this, tourism is considered, socially and economically, the largest industry in the world, being also one of the major industries in the world affecting employment (Theobald, 2013), since tourism accounts for a large portion of the Gross Domestic Product (GDP) of many nations (Jayapalan, 2001). As can be seen in Figure 1, since 1950, the number of international tourist arrivals has been growing immensely throughout the years, with a slight exception in the years 2020, 2021, and 2022, due to the presence of the Covid-19 pandemic.

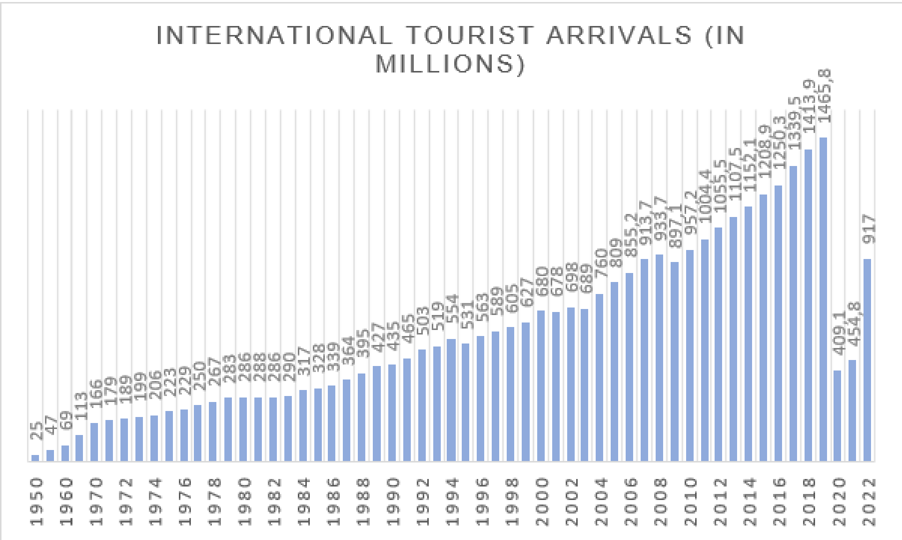

Figure 1 - Number of International Tourist Arrivals Worldwide, 1950-2022.

Source: Statista. (2023, February 2)

The growth of the tourism industry has led to an increase in the number of destinations, especially in underdeveloped countries. Tourism is seen as a potential source of income and job creation in these areas. Sustainable tourism can bring many benefits, including wealth redistribution, rural-urban integration, improved international reputation, increased foreign investment, preservation of natural resources, promotion of harmony and peace, and technological development. However, if not managed properly, tourism can also have negative impacts such as misuse of resources, invasion of privacy, crime, and degradation of habitats (Gonap, 2018). Due to the increase in tourism, the practice of sustainable tourism is becoming more and more noticeable. Ecotourism aims to promote sustainable tourism where visitors can enjoy attractions without harming the environment, while also benefiting local residents. Proper management of resources is essential to achieve sustainable tourism and ensure that the economy, society, and culture are balanced with environmental preservation (Jaini et al., 2012). Figure 2 presents more in-depth some advantages and disadvantages of tourism in social and economic manners.

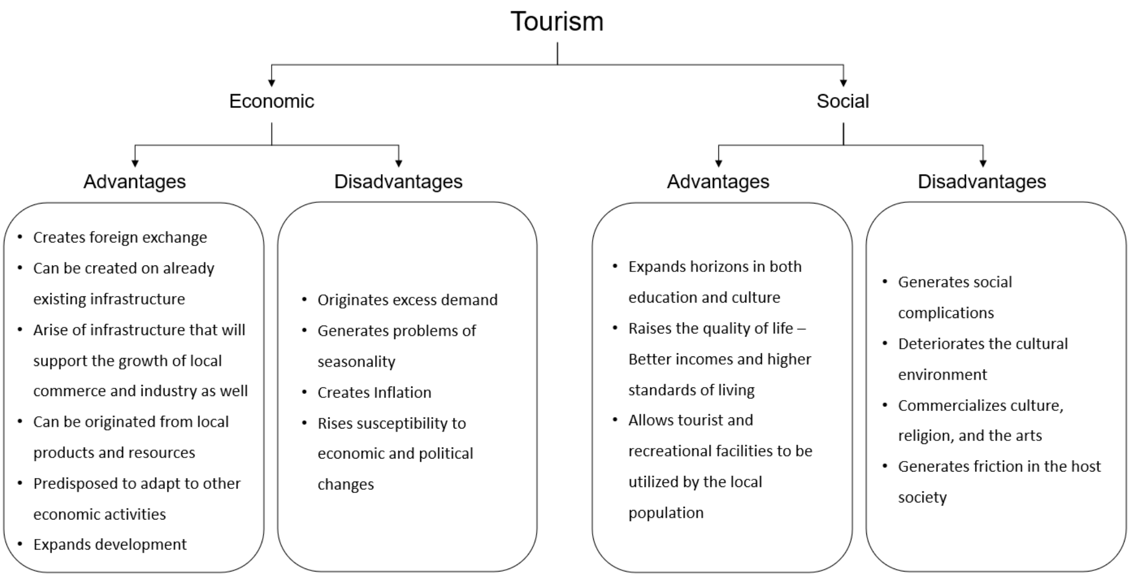

Figure 2 - Social and Economic Advantages and Disadvantages of Tourism.

Source: Goeldner and Ritchie. (2003)

Although various statistics and data regarding tourism are available, many believe that one of the main problems of this industry is the difficulty in obtaining this information, due to the lack of certainty originated from the sector's fragmentation and diversity (Theobald, 2013). This not only depends on the way that tourism is defined, which will be deepened in the following section, but also on the fact that it is just not possible to determine with reliability if certain data is linked only to tourists since everything available to them, regarding what the tourism industry offers (transportation, restaurants, accommodations, attractions, etc.), is not exclusive and can also be used by any other member of society (Gonap, 2018). As stated before, even though the large diversity of the tourism sector can represent a problem, it is also one of the main advantages of its economic development, since it can adapt to any type of country, religion, culture, or landscape (Theobald, 2013).

2.2. Definition

As many have stated, defining the word “tourism” can be rather challenging, since the term is comparable to “education”, which both refer to an area of academic study or the illustration of occurrences in the outside world (Tribe, 1997). Even among corporate and government executives that work in tourism, travel, and leisure on a daily basis, it was found that many of the terms used often in the industry have hazy definitions and lack agreement, due to the fact that tourism has been proven to have additional meanings beyond the norm (Hunt & Layne, 1991; Tribe, 1997).

When tourism is seen as a study, the majority of academic authors have the tendency of customizing their definitions to their particular aims, associated with fields like economics, sociology, culture, and geography, among others, which is not entirely wrong since tourism is believed to be a science that is naturally carried out with the help of such fields (Tribe, 1997; Lickorish & Jenkins, 2007; Panosso Netto, 2009; Theobald, 2013, Yu et al., 2012). Due to this, Panosso Netto (2009) states that it's impossible for one researcher to develop a comprehensive theoretical model that can account for all the aspects of tourism. However, such a discrepancy may have major repercussions since it casts doubt on the public's perception of the veracity of tourist data and impact studies which, in other words, means that this possible variation can reduce the credibility of statistical reports that aim to support and explain the distribution of funding for tourism (Yu et al., 2012). This makes it almost impossible to achieve a unanimous decision regarding the definition, even though some believe that tourism is a broad term that includes all of a tourist's activities, thus it doesn't need to be precisely defined (Hunt & Layne, 1991).

Nevertheless, a more detailed definition of tourism is necessary for various reasons. For research purposes, a clear definition is needed to analyze the phenomenon systematically. For statistical purposes, a definition is necessary before measuring tourism. Governments may also need to define tourism to regulate it properly. Finally, a specific definition of tourism may facilitate the creation of industrial organizations and market analyses. (Panosso Netto, 2009). Theobald (2013) argues that having a clear definition of tourism sets boundaries for research material and establishes accepted standards and, without such standards, it is difficult to determine the economic impact of tourism on local, national, and international economies. One of the many things that make this definition so complex is the fact that tourism is an intricate sector since it does not provide a product but a set of services making it a “collection of industries, enterprises, resources, and attractions” (Kaiser & Helber, 1978:4-5 in Leiper, 1979). Conventionally, two fundamental components make up tourism: a dynamic element (involving the travel to the destination), and a static element (involving the stay at the destination) (Leiper, 1979; Gonap, 2018). It is also believed that tourism can be defined by three major dimensions: the goal of the trip, the distance of the journey, and the duration (Leiper, 1979; Hunt & Layne, 1991; Yu et al., 2012; Theobald, 2013). Theobald (2013) even purposes two more elements that could be an addition to the already described dimensions: the place of residence of the traveler and the transportation method.

Leiper (1979) proposed three different perspectives to define tourism: economic, technical, and holistic. The economic perspective only considers monetary or commercial aspects, ignoring the human element and geographical or temporal components. To address these limitations, the industry developed technical definitions for various purposes, such as statistics and legislation. However, these definitions have taken different approaches to the three factors that make up the idea of tourism. Finally, the holistic strategy aims to include all these factors to provide a more comprehensive understanding of tourism. In Tribe's (1997) view, tourism can be divided into three segments: travel or tourism, the academic study of tourism, and tourism education and training. The rise of the academic community studying tourism has led to the development of a body of knowledge known as the study of tourism. Tourism education and training have emerged as a result of the creation of courses in tourism, aiming to provide individuals with the skills and knowledge needed to succeed in the industry. Lickorish and Jenkins (2007) and Theobald (2013) categorized tourism into three main types: domestic, inbound, and outbound tourism. Domestic tourism involves citizens traveling within their own country, inbound tourism involves visitors traveling to a country that is not their own, and outbound tourism is when people from a certain country travel to another country. The authors also explain that internal tourism includes domestic and inbound tourism, national tourism contains domestic and outbound tourism, and international tourism involves inbound and outbound tourism.

With this, some definitions of Tourism can be presented. Burkart and Medlik (1981) in Lickorish and Jenkins (2007) defined it as the phenomenon arising from temporary visits (or stays away from home) outside the normal place of residence for any reason other than furthering an occupation remunerated from within the place visited. Mathieson and Wall (1982: I) in Tribe (1997) established it as the temporary movement to destinations outside the normal home and workplace, the activities undertaken during the stay, and the facilities created to cater to the needs of tourists. Gonap (2018) established tourism is a multi-faceted phenomenon that involves moving to and staying in destinations outside the normal place of residence for the purpose of recreation, business, education, health, etc. More definitions can be found in Table A.21 in Appendix A.

After all of the definitions presented, it is visible that, to better understand tourism, the term “tourist” is a concept that also has to be understood. Tourist activity requires staying away from the usual place of habitation for at least one night or more than 24 hours (Gonap, 2018). The overnight-stay criteria and the voluntary use of one’s time and financial resources usually separate tourists from day trippers (Leiper, 1979). Since it was concluded that motivation, or the aim of the journey, is one of the most crucial components in characterizing a tourist, another feature that characterizes tourists is the type of journeys they take (Hunt and Layne, 1991; Gonap, 2018). A tourist is someone who goes on a temporary and optional trip for pleasure, requiring at least one overnight stay away from their usual place, excluding trips primarily taken for business purposes with the intent of returning to the starting point (Leiper, 1979; Yu et al., 2012). The idea that tourists are not in their usual environment is supported by their tendency to visit well-known destinations without interacting with locals. To determine if someone is a tourist, the concept of "threshold" is often used, which is a fixed distance that is considered significant enough for the person's travel to be categorized as tourism. (Yu et al., 2012). The concept of a tourist is one of two categories that a visitor may be considered, with the second being an excursionist. The difference between the two is that an excursionist is considered to be a same-day visitor, while a tourist requires at least one night away (Lickorish & Jenkins, 2007; Theobald, 2013).

The study of tourism is important to gain knowledge and new perspectives. However, current research only covers a small part of the industry, and there may be undiscovered aspects. Additionally, there is a connection between the study and practice of tourism, which highlights the need for clear definitions and boundaries in tourism research to understand the components of the industry that are investigated (Tribe, 1997).

2.3. Tourism and Accommodation

2.3.1. Europe

Europe is the most visited area in the world due to its rich cultural history and major tourist sites, accounting for 50% of all foreign tourist arrivals, 81% of all international arrivals in Europe and 40% of all arrivals worldwide are made up of the 28 members of the European Union (EU). Sustained development in tourism has greatly boosted GDP, job creation, and the balance of payments in many European economies, making tourism one of the foundational pillars of the EU's plan for inclusive growth and jobs. In 2016, the EU received 500 million international overnight guests, accounting for 40% of all tourists globally, and generated 342 billion euros in revenue through international travel, equating to 31% of total tourist revenue (UNWTO, 2018).

As said before, tourism is an aggregation of various sectors and industries. With this, the accommodation industry is one of the crucial aspects of tourism, as tourists' satisfaction with the service they receive heavily impacts their willingness to return or recommend it to others. The quality of the service provided by the accommodation industry can also influence tourists' overall opinions of the destination (Viskers and Znotina, 2017).

According to Eurostat, there were 608,000 accommodation facilities in the EU in 2016, of which 202,000 (33%) were hotels, 378,000 (62%) were vacation rentals and other short-term accommodation, and 28,000 (5%), camping sites and RV/trailer parks. 31 million beds were available in these facilities. Two-thirds of the EU's total bed capacity is accounted for by its biggest members, which include France, Italy, the United Kingdom, Spain, and Germany. The number of nights spent overall at EU accommodation facilities climbed from 2.4 billion in 2010 to 3.1 billion in 2016, led by 1.5 billion nights spent by tourists from outside the EU in 2016. (UNWTO, 2018).

In Figure 3, some data from 2021 is presented regarding the number of nights that tourists from different regions or countries of Europe spend at tourist accommodation establishments.

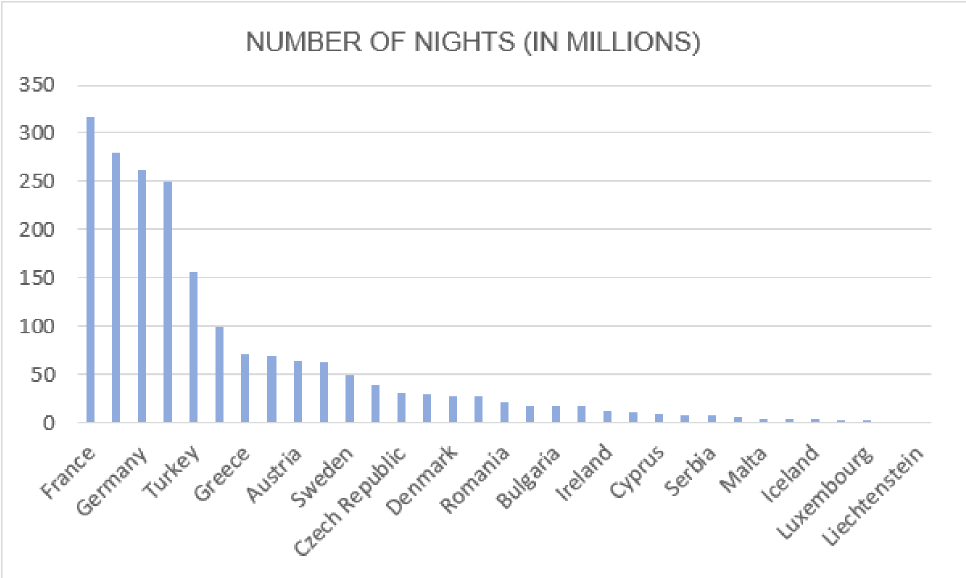

Figure 3 - Nights Spent at Tourist Accommodation Establishments by Country/World Region of Residence of the Tourist.

Source: Eurostat. (2023, January 5)

2.3.2. Portugal

Portugal's economy is primarily reliant on the tourism sector to provide income and employment since it is a country that attracts a lot of tourists each year by utilizing its favorable geographic location and the variety of its culture and nature (Portal Diplomático, n.d.). About 8% of Portugal's GDP is produced by the tourist industry, which also accounts for 10% of all employment and significantly lowers the country's balance of payments (Proença and Soukiazis, 2005). Overnight stays have climbed at the fastest pace in history during a span of nine years, rising from 37 million in 2010 to 70 million in 2019, the highest amount ever. Additionally, over the same nine years gap, tourism-related income has increased at an average annual rate of 10.3%, going from $7.6 billion in 2010 to 18.4 billion in 2019 (Turismo de Portugal, 2021).

Figure 4 – Number of International Arrivals and Overnight Stays in Portugal, 2015 - 2022

Source: Statista. (2023, April 6)

Figure 4 shows a significant increase in tourist arrivals and overnight stays, except for the years 2020 and 2021, when the COVID-19 pandemic impacted the travel industry. International demand sharply decreased with 12.3 million overnight stays by foreigners (-74.9%) due to travel restrictions in 2020. The domestic market also recorded a decrease in overnight stays (-35.4%) compared to 2019. The decrease in revenue (-57.6%) resulted in a loss of 10 billion euros for the economy in 2020 (Turismo de Portugal, 2021).

In 2021, the COVID-19 pandemic had a significant impact on the tourism industry, with confinement measures affecting travel activity. Although the industry performed better than in 2020, there were still 45.8% fewer visitors than in 2019. Despite a 36.9% increase in visitors compared to 2020, the industry still lagged behind pre-pandemic levels (INE, 2021a).

As of July 31st, 2021, there were 6,571 tourist accommodation facilities in operation, which reported an increase in visitor movements of 20.2% over the year before but a decline of 8.2% over 2019. With 14.5 million visitors and 37.3 million overnight stays, tourist accommodation facilities saw a rise of 38.6% and 44.7%, respectively, over the prior year but a decline of 46.7% and 46.8% over 2019. 1.4 million campers and 4.9 million overnight stays were recorded in campgrounds, representing an increase of 22.1% and 16.6%, respectively, over the previous year but still less than the levels from 2019 (INE, 2021b).

Considering the accommodation establishments (tourist accommodation establishments, camping and holiday campsites, and youth hostels), some data regarding tourist accommodation means in 2021 are presented in Table 1. These data are based on the results of the Survey on the Stay of Guests in Hotels and Other Accommodation ("Inquérito à Permanência de Hóspedes na Hotelaria e outros alojamentos" - IPHH), the Survey on the Stay of Campers in Campsites ("Inquérito à Permanência de Campistas em Parques de Campismo" - IPCAMP), and the Survey on the Stay of Colonists in Holiday Camps ("Inquérito à Permanência de Colonos nas Colónias de Férias" - IPCOL). This information solely relates to lodging options for tourists, such as hotels, inns, and dwellings in rural regions with ten or more beds (INE, 2021b).

In February 2023, Portugal's tourist accommodation industry experienced a significant boost with 1.7 million visitors, 4.0 million overnight stays, and 245.7 million € in overall income, representing a 33.0% increase in visitors and a 60.3% increase in overall income compared to the same period in 2022. Albufeira, a popular municipality, recorded fewer overnight stays overall but still remains among the top municipalities with the highest representativeness. Total overnight stays increased by 52.9% in January and February of 2023 compared to the same period in 2022, leading to a 75.6% increase in total income and a 77.9% increase in accommodation revenue. These figures are higher than those recorded in the same period in 2020 (INE, 2023).

Table 1 - Results for Most Tourist Accommodations, 2019-2021

Source: INE. (2021b)

Global Results	Units	2019	2020	2021
Establishments	nº	7155	5467	6571
Accommodation capacity	nº	643308	539917	604118
Guests	10^3	29495,4	11668,3	15974,6
Slepts	10^3	77822,7	30283,8	42608
Average stay	nº of nights	2,64	2,6	2,67
Occupancy rate - bed (Net)	%	47,3	24,1	31,1
Total income	10^6 €	4295,8	1445,7	2330,3
Room revenue	10^6 €	3229,9	1076,4	1752,3
Average return per available room	€	49,4	22,6	32,6
Average return per occupied room	€	89,2	77,3	88,2

2.4. Chapter Conclusion

In summary, this chapter has examined the historical evolution of travel and tourism, emphasizing its pivotal role in the global economy. The tourism industry has become the largest worldwide, encompassing diverse dimensions and perspectives that necessitate a clear definition for research and statistical purposes. Within the EU and Portugal, tourism has exhibited substantial growth, serving as a vital source of income and employment. However, the COVID-19 pandemic has severely affected the industry, leading to economic losses. The recovery of the tourism sector in Portugal is a positive sign, but sustainability and minimizing negative impacts should be prioritized. Future research should focus on regional impacts and effective management strategies for maximizing benefits. Overall, the tourism industry remains a crucial force, and its development, efficiency, and sustainability require attention from policymakers, stakeholders, and researchers.

3. State-of-the-Art

This chapter starts with section 3.1. which introduces some concepts regarding efficiency and effectiveness. In 3.2., performance evaluation methodologies are described, along with a more detailed description of said methodologies in subsection 3.2.1., and a more in-depth study of the Data Envelopment Analysis (DEA) in subsection 3.2.2., since it is going to be the approach used later. In section 3.3., a brief explanation on what is the Malmquist Productivity Index can be found. In section 3.4. presents the literature review of this dissertation, which is extremely necessary to understand the evolution of the various concepts presented and that will be needed in this work. Finally, section 3.5. describes the chapter’s conclusions.

3.1. Efficiency

Efficiency was found as difficult to define as tourism, since, as the latter concept, it can be defined according to the field where it is inserted. Banton (2022) defined efficiency as the ability to achieve the highest level of output using the fewest possible inputs while minimizing waste and unused resources. It applies to various resources, including time, money, human capital, manufacturing equipment, and energy sources. It can be calculated as the ratio of usable output to total input, and a process is considered efficient when nothing is wasted, and all processes are optimized. According to Hubbell (2007), efficiency is a key measure of how activities are performed, linking quality, delivery, and strategy. Effective operations produce desired outcomes at a high level of quality while using the least amount of a scarce resource. The concept of efficiency evaluates whether tasks are being carried out clearly and effectively, resulting in the desired strategic outcomes at the appropriate level of quality.

However, the discussion of efficiency began with Farrell (1957) and Charnes et al. (1978) (Førsund, 2018). Efficiency, often known as the frontier function, was first described by Farrell (1957) as the proportionate scaling necessary to transfer observations from an inefficient unit onto an efficient production function. As opposed to this, Charnes et al. (1978) limited the ratio to be less than or equal to the ratio of the most efficient operation, which is normalized to 1. They did this by utilizing an index of weighted outputs on weighted inputs.

Basically, efficiency is one of the key concepts in evaluating and measuring an organization's performance, but so is effectiveness, which often leads to some inconsistency regarding the definition of these concepts (Mouzas, 2006). Efficiency is commonly associated with doing things correctly, while effectiveness is associated with doing the right things. Effectiveness is dependent on how well the goals are achieved, making measures of effectiveness crucial for evaluating how well business units perform in relation to their efforts toward strategic goals (Asmild, 2007).

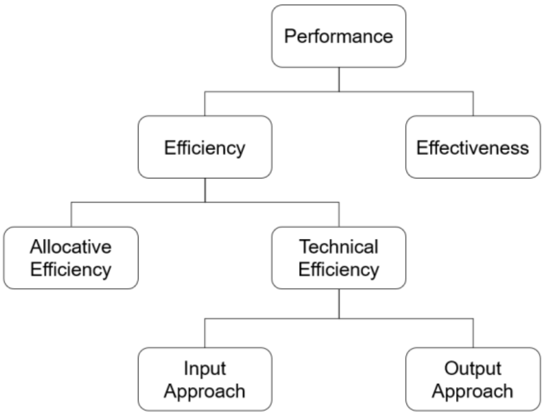

Figure 5 - Types of Efficiency

Source: Porcelli. (2009)

Moreover, as already stated, it is believed that efficiency can have various definitions according to where it is going to be applied. As stated by many, efficiency can be of two types: allocative and technical, which can be seen in Figure 5. Technical efficiency refers to achieving the maximum possible improvement in outcome from a set of resource inputs and using the fewest inputs possible to achieve a given level of outputs. The term allocative efficiency refers to the optimal combination of inputs that leads to the lowest possible cost of production. It considers the distribution of health outcomes among the community as well (Farrell, 1957; Palmer & Torgerson, 1999). The methods commonly used to assess the efficiency performance will be presented in the next subsection.

3.2. Performance Evaluation Methodologies (PEM)

Parametric and non-parametric performance evaluation methodologies are the two basic categories identified by Marques (2011). Both of these strategies fall into two categories: those that employ reference frontiers and those that do not. While non-parametric procedures do not require parameter inference from a sample, parametric ones must. Depending on whether they consider random error or not, these approaches may be further divided into a stochastic or deterministic methodology, and efficient frontier or average adjustments. In Figure 6, it is shown the hierarchy of said approaches and the models that integrate them.

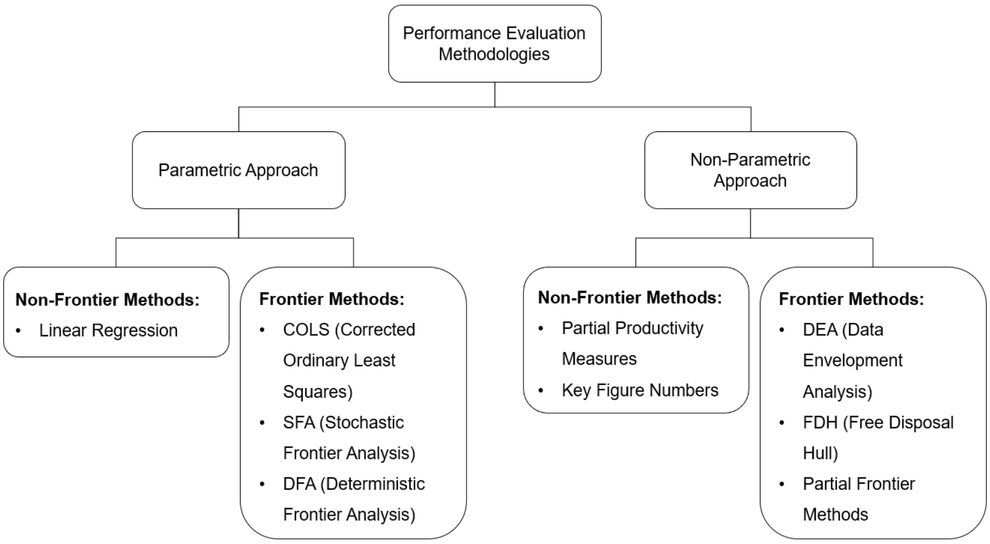

Figure 6 - Performance Evaluation Methodologies

Source: Marques. (2011)

3.2.1. Parametric and Non-Parametric Approaches

Performance evaluation methodologies aim to assess the efficiency of various decision-making units (DMUs) in comparison to a frontier. Drake and Simper (2005) have proposed two primary methods to construct an efficient frontier – a parametric approach and a non-parametric approach. Both methods can be employed to generate an efficiency ranking that ranges from 0, indicating poor practices, to 1, representing the best practices. Linear regression, corrected ordinary least squares (COLS), stochastic frontier analysis (SFA), and deterministic frontier analysis (DFA) are parametric methods that need a function estimation to define the production frontier and measure errors. On the contrary, data envelopment analysis (DEA), which is a non-parametric method, is based on empirical observations and requires multiple observations to construct a production frontier. Depending on whether an efficient frontier is established or not, the classification is based on a comparison with the best practices or an average adjustment, respectively (Marques & Silva, 2006). This section will compare the two most commonly used models in efficiency evaluation studies, SFA and DEA, which are used in the parametric and non-parametric approaches, respectively (Chen, 2007).

Both the parametric and non-parametric approaches for evaluating efficiency begin with defining the goal, which can be to maximize outputs given fixed inputs, minimize inputs given fixed outputs, or maximize profits given certain outputs. The next step is to estimate the efficient frontier, which is where the two methods differ. The efficient frontier is then used to compare the efficiency of different decision-making units (Drake & Simper, 2005).

Moreover, Drake and Simper (2005) explain that non-parametric approaches, such as DEA, construct the efficient frontier using linear programming techniques without any prior assumptions. Conversely, parametric approaches, like SFA, estimate the efficient frontier function based on statistical data and parameters. This approach, according to Coeli et al. (2005), presents some advantages and disadvantages against DEA since it considers the random disruptions in the production process and enables statistical hypothesis testing but the decomposition of the random disturbance and technical inefficiency terms can be influenced by the distribution function selected. However, DEA methodology offers an advantage in evaluating tourism services' efficiency as it allows for problems with multiple outputs, while SFA methodology is limited to only one output, which is a disadvantage in the context of tourism which requires various problems with multiple inputs and outputs.

According to Kuah and Wong (2011), DEA is a favored method for assessing the performance of non-profit institutions, including state-provided services such as hospitals, water sector services, and police services, because it can handle multiple input-output problems without any predefined hypotheses. This shows that this method is also probably the best for analysis in the tourism industry. However, as stated by Chen et al. (2010), DEA has a major disadvantage when compared to SFA since it doesn't consider random errors, whereas SFA models segregate the deviations from the efficient frontier into statistical noise or inefficiencies. The DEA approach considers all deviations as inefficiencies, which can be a disadvantage.

In conclusion, the non-parametric DEA approach will be used in the study of the tourism industry due to its nature and the differences stated between the DEA and the SFA methodologies. A more in-depth analysis of the DEA method will be presented in the next subsection.

3.2.2. DEA Methodology

According to Thanassoulis (2001), for the DEA methodology to be applicable to a problem, the following basic procedures should be fulfilled: the organizations being studied must be homogeneous, with the study units having comparable objectives and performing the same tasks in similar external environments; the variables such as inputs and outputs must be the same for all study units, with variations only in their magnitudes.

DEA evaluates the efficiency of DMUs that have multiple inputs and outputs by maximizing the ratio of the weighted sum of outputs to inputs while ensuring that similar ratios for each DMU are less than or equal to 1, according to Charnes et al. (1978). DEA is a non-parametric technique that uses linear programming to assess DMU efficiency. It considers multiple inputs and outputs in measuring efficiency. According to Cook and Zhu (2005), DEA is a method used to evaluate the performance of DMUs by assessing how their inputs are converted into outputs. The authors explain that the efficiency of DMUs can be calculated by comparing the weighted sum of inputs with the weighted sum of outputs.

The DEA methodology has some drawbacks such as a higher probability of considering more DMUs efficient as the number of variables analyzed increases, difficulty in formulating statistical hypotheses, and poor performance in searching for "absolute" efficiency since the frontier is estimated based on observed data and not on the "optimum". Moreover, DEA evaluates relative efficiency instead of absolute efficiency, and it assumes that all DMUs that are not on the frontier are inefficient. Finally, hypothesis testing is not possible with DEA (Dyson et al., 2002; Sarafidis, 2002).

DEA models can be categorized into two main types: input orientation models, which aim to minimize the consumption of inputs while maintaining a given level of outputs, and output orientation models, which aim to maximize the level of outputs given a certain level of inputs (Thanassoulis, 2000; Barros & Athanassiou, 2004). DEA models are classified into two types, input orientation, and output orientation, and each type can be further divided into two subcategories: Constant Returns to Scale (CRS)-based models (also called CCR models) and Variable Returns to Scale (VRS)-based models (also called BCC models). The CCR models are named after their authors, Charnes, Cooper, and Rhodes (Charnes et al., 1978), while the BCC models are named after Banker, Charnes, and Cooper (Banker et al., 1984).

3.2.2.1. CCR Model

The CCR model, proposed by Charnes, Cooper, and Rhodes, is based on the concept of frontier analysis by Farrell (1957) and uses CRS technology to measure the efficiency of decision-making units (DMUs). The model generates a relative efficiency index by maximizing the ratio between the weighted sum of outputs and inputs subject to the restriction that other DMUs cannot achieve an efficiency level greater than one. Fractional programming is used to assign different weights to the inputs and outputs of each DMU to maximize their efficiency, and the resulting efficiency index is based on a comparison of the inputs and outputs of all DMUs (Charnes et al., 1978).

The model assumes the existence of *n* DMUs, each of which consumes x_{ij} inputs and produces y_{rj} outputs to be evaluated. The efficiency of a particular DMU_0 is measured in relation to the efficiencies of all other DMUj where j=1…n. The weights of inputs and outputs are denoted as v_i and u_r, respectively, and the inputs and outputs of DMU_0 are denoted as x_{r0} and y_{r0} in the model formulation (Cooper et al., 2011). This formulation can be seen in Table 2.

However, this formulation has the issue of producing an endless number of optimum solutions so, due to this issue, a new model called the primal model or multiplier model, which employs linear programming rather than fractional programming, has been developed, which can be seen in Table 3 (Cooper et al., 2011).

Table 2 - Formulation of the DEA Methodology for the CRS Model.

Source: Cooper et al. (2011)

DEA - CCR (Input Oriented)	DEA - CCR (Output Oriented)
$Max\, h_0 = \dfrac{\sum_r u_r y_{r0}}{\sum_i v_i x_{i0}}$ $Subject\ to:$ $\dfrac{\sum_r u_r y_j}{\sum_i v_i x_{ij}} \leq 1, j = 1,\ldots,n$ $u_r\ and\ v_i \geq 0 \forall r,i$	$Min\, h_0 = \dfrac{\sum_i v_i x_{i0}}{\sum_r u_r y_{r0}}$ $Subject\ to:$ $\dfrac{\sum_i v_i x_{ij}}{\sum_r u_r y_{rj}} \geq 1, j = 1,\ldots,n$ $u_r\ and\ v_i \geq 0 \forall j,i$

Table 3 – Formulation of the DEA Methodology for the Primal CRS Model.

Source: Cooper et al. (2011)

Primal (Multipliers)	
DEA - CCR (Input Oriented)	**DEA - CCR (Output Oriented)**
$Max\, z = \sum_{r=1}^{s} u_r y_{r0}$ $Subject\ to:$ $\sum_{i=1}^{m} v_i x_{i0} = 1$ $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ $u_r\ and\ v_i \geq 0$	$Min\, q = \sum_{i=1}^{m} v_i x_{i0}$ $Subject\ to:$ $\sum_{i=1}^{m} u_r y_{r0} = 1$ $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0$ $u_j\ and\ v_i \geq 0$

Based on the primal model, Table 4 represents the dual model. The weights of the inputs and outputs of each DMU are denoted by λ_j.

Table 4 - Formulation of the DEA Methodology for the Dual CRS Model.

Source: Cooper et al. (2011)

Dual	
DEA - CCR (Input Oriented)	**DEA - CCR (Output Oriented)**
$\theta^* = Min\,\theta$ $Subject\ to:$ $\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{i0},\ i = 1,\dots,m$ $\sum_{j=1}^{n} y_{rj}\lambda_j \le y_{r0},\ r = 1,\dots,s$ $\lambda_j \ge 0,\ j = 1,\dots,n$	$\theta^* = Max\,\theta$ $Subject\ to:$ $\sum_{j=1}^{n} x_{ij}\lambda_j \le x_{i0},\ i = 1,\dots,m$ $\sum_{j=1}^{n} y_{rj}\lambda_j \le \theta y_{r0},\ r = 1,\dots,s$ $\lambda_j \ge 0,\ j = 1,\dots,n$

3.2.2.2. BCC Model

In 1984, Banker and colleagues suggested an expansion to the CCR model that enabled the detection of whether there were increasing or decreasing variable returns to scale (VRS). This led to the development of the BCC models, which incorporated the possibility of the existence of VRS technologies, regardless of whether they were increasing or decreasing, into these formulations. The BCC model introduces a constraint that requires the way DMUs are combined to be convex, ensuring that entities being evaluated are only compared to others of the same size. This convexity constraint, expressed as $\sum_k \lambda_k = 1$, is the only difference between the BCC and CCR models. The primal model with this constraint is shown in Table 5, while the dual model is presented in Table 6.

Table 5 – Formulation of the DEA Methodology for the Primal VRS Model.

Source: Cooper et al. (2011)

Primal (Multipliers)	
DEA - BCC (Input Oriented)	**DEA - BCC (Output Oriented)**
$Max\, z = \sum_{r=1}^{s} u_r y_{r0} - u_0$ $Subject\ to:$ $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \le 0$ $\sum_{i=1}^{m} v_i x_{i0} = 1$	$Min\, z = \sum_{i=1}^{m} v_i x_{i0} - v_0$ $Subject\ to:$ $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \le 0$ $\sum_{r=1}^{s} u_r y_{r0} = 1$

Table 6 – Formulation of the DEA Methodology for the Dual VRS Model.

Source: Cooper et al. (2011)

Dual	
DEA - CCR (Input Oriented)	**DEA - CCR (Output Oriented)**
$Min\,\theta$	$Max\,h_0$
$Subject\ to:$	$Subject\ to:$
$\theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j \geq 0$	$h_0 y_{j0} - \sum_{j=1}^{n} y_{rj}\lambda_j \leq 0$
$-y_{r0} + \sum_{j=1}^{n} y_{rj}\lambda_j \geq 0$	$-x_{r0} + \sum_{j=1}^{n} x_{rj}\lambda_j \geq 0$
$\sum_{j=1}^{n} \lambda_j = 1$	$\sum_{j=1}^{n} \lambda_j = 1$
$\lambda_j \geq 0$	$\lambda_j \geq 0$

3.3. Malmquist Productivity Index

The Malmquist Productivity Index (MPI), also known as Total Factor Productivity Index (TFPCH), introduced by Malmquist in 1953, is a ratio of distance functions. It is calculated by dividing the total VRS efficiency of a second period by the VRS efficiency of a first period. The MPI provides a measure of changes in efficiency over time and allows for comparisons between different periods (Malmquist, 1953).

The MPI is frequently employed to evaluate productivity improvements over time. It allows for the comparison of efficiency values for a particular DMU across time. The Malmquist index enables the measurement of efficiency changes over time while the DEA technique only offers efficiency levels for certain years (Caves et al., 1982).

Relying solely on data from a single year may lead to biased conclusions due to the omission of market dynamics. It is important to consider that DMUs can vary in efficiency across different periods, with some being inefficient and others being efficient. Therefore, considering multiple time periods provides a more comprehensive understanding of efficiency fluctuations (Chen & Ali, 2004).

In conclusion, the MPI is an effective instrument for determining how total factor productivity has changed over time. It enables the breakdown of this index into components representing technical change (TECH) and technological change (TECCH) (Färe et al., 1994):

$$\text{TFPCH} = \left(\sqrt{\frac{D_0(x_v^t, y_v^t)}{D_t(x_v^t, y_v^t)} \cdot \frac{D_0(x_v^0, y_v^0)}{D_t(x_v^0, y_v^0)}}\right) \cdot \left(\frac{D_t(x_v^t, y_v^t)}{D_0(x_v^0, y_v^0)}\right) = \text{TECH} * \text{TECCH}$$

The mentioned variables represent different distances and quantities related to the analysis of a DMU over two periods, namely period 0 and period t, where:

- D_0 - Distance function relative to the frontier of period 0;
- D_t - Distance function relative to the frontier of period t;
- $y_v{}^0$ - Quantity of virtual output of the DMU under analysis in period 0;
- $x_v{}^0$ - Virtual input quantity of the DMU under analysis in period 0;
- $y_v{}^t$ - Quantity of virtual output of the DMU under analysis in period t;
- $x_v{}^t$ - Virtual input quantity of the DMU under analysis in period t;
- D_0 $(x_v{}^0, y_v{}^0)$ - Distance of the DMU in period 0 relative to the frontier of period 0;
- D_0 $(x_v{}^t, y_v{}^t)$ - Distance of the DMU in period t relative to the frontier of period 0;
- D_t $(x_v{}^0, y_v{}^0)$- Distance of the DMU in period 0 relative to the frontier of period t;
- D_t $(x_v{}^t, y_v{}^t)$ - Distance of the DMU in period t relative to the frontier of period t.

The traditional MPI mostly focuses on radial efficiency and requires scoring based on the orientation (input or output) selected. The output orientation will be used in this study's investigation of municipalities specifically. A rise in performance between period t and period t+1 is indicated by a MPI greater than 1. If the MPI is 1, there has been no performance change between the two periods. In contrast, a decline in performance is indicated if the MPI is smaller than 1. Technical and technological change make up the two components of the Malmquist Total Factor Productivity index. Due to the fact that these factors' values might change over time and across producers (in this example, municipalities), they are referred to as local indices. Municipalities may simultaneously exhibit rising and declining trends technological efficiency at a particular time. Similar patterns of technological development may be seen in some areas throughout time, while others may see a slowdown (Färe et al., 1994)

Färe et al. (1994) highlighted the capacity of the Malmquist Total Factor Productivity index to be divided into the sum of the index of technical efficiency change and the index of technological development as one of its key characteristics. This decomposition offers flexibility in evaluating and comprehending the trends in the said index over time and among municipalities.

As the municipality approaches the border, a value of (TECH) larger than 1 implies an increase in technical efficiency from period t to period t+1. In contrast, if (TECH) is smaller than 1, it denotes a decline in technical efficiency and a greater separation of the municipality from the boundary. A number larger than 1 for (TECHH) indicates increased productivity in the accommodation sector, with all local housing in the municipality generating more services in period t+1 than in period t. If (TECHH) is greater than 1, however, it shows an increase in productivity within the municipality's accommodation industry between the two time periods (Färe et al., 1994)

3.4. Literature Review

Cracolici et al. (2008) suggest that the efficient management of inputs is a key factor in achieving the desired output and ensuring long-term success for tourist destinations. Similarly, according to Corne (2015), hotels play a critical role in the tourism industry, and their competitiveness in attracting tourists is essential for the overall efficiency of tourism. Thus, evaluating the efficiency of hospitality is crucial in assessing the efficiency of tourism. To further understand the application of the aforementioned concepts around the tourism industry, an extensive search was performed to find the most representative articles regarding this dissertation's theme.

The main platforms used to conduct this search were Mendeley, Google Scholar, and Elsevier ScienceDirect, with special attention to the first one, which was the dominant platform used throughout this analysis due to some characteristics, such as its organization and straightforwardness in searching the required articles, for example. To do such a search, some keywords were used as a base such as "efficiency analysis", and "tourism". The articles chosen had as selection criteria their relevance in the matter and their citations, meaning the number of times the article has already been cited, which can be sorted in the Mendeley platform, with no more than 10 years.

With this, the goal is to understand the evolution of the concepts, what has been explored and studied, and what can still be done, or in other words, what is the literature gap. In this literature review, 13 articles were analyzed, which can be found in Table 7. These articles have a period of 7 years (2014 to 2021), where 2014 and 2016 represent approximately 46,2% of the analyzed articles.

Table 7 – Resume of Articles from Literature Review

Year of Article	Author(s)	Title	Nº of Regions/Accomodations Studied	Method	Inputs	Outputs
2014	Félix Luis Agabo-Mateos, Bernabé Escobar-Pérez, Antonio Lobo-Gallardo	Measuring efficiency of the youth hostel sector in Andalusia using an adapted DEA model	18 Youth Hostels (Andalusia)	DEA	Labor costs; Number of beds; Total operational costs	Room revenue; F&B revenue; Total revenue
2014	Bernardino Benito, José Solana, Pilar López	Determinants of Spanish regions' tourism performance: a two-stage, double-bootstrap data envelopment analysis	17 Regions (Spain)	DEA	Accomodation capacity; Tourist Arrivals	Number of bed-nights
2014	Claudio Detotto, Manuela Pulina, Juan Gabriel Brida	Assessing the productivity of the Italian hospitality sector: a post-WDEA pooled-truncated and spatial analysis	19 Regions and 2 Provinces (Italy)	Window-DEA	Labor costs; Gross fixed investment	Sales revenue; Value added
2015	Ricardo Samuel Lisboa Pereira Oliveira, Maria Isabel Craveiro Pedro, Rui Domingos Ribeiro da Cunha Marques	Avaliação da eficiência das empresas hoteleiras do Algarve pela metodologia análise de envoltória de dados (DEA)	28 Hotels (Portugal)	DEA	Number of bedrooms; Number of employees; F&B capacity; Other costs; Personnel costs; Capital costs	Total revenue
2016	Yasuo Ohe, Nicolas Peypoch	Efficiency analysis of Japanese Ryokans: A window DEA approach	9 Regions (Japan)	Window-DEA	Number of employees; Number of rooms	Total revenue; Total number of overnight stays
2016	José Solana-Ibáñez, Manuel Caravaca-Garratón, Lorena Para-González	Two-stage data envelopment analysis of Spanish regions: efficiency determinants and stability analysis	17 Regions (Spain)	DEA	Number of beds available; Number of nights a traveler stayed at one establishment	Number of people staying at least one night at an establishment

Table 7 – Resume of Articles from Literature Review (Continuation)

Year of Article	Author(s)	Title	Nº of Regions/Accomodations Studied	Method	Inputs	Outputs
2016	Amar Oukil, Nabil Channouf, Asma Al-Zaidi	Performance evaluation of the hotel industry in an emerging tourism destination: The case of Oman	58 Hotels (Oman)	Two-staged DEA	Number of beds; Salary of employees	Annual revenue; Number of guests; Number of nights; Occupancy rate
2017	Calogero Guccio, Domenico Lisi, Marco Martorana, Anna Mignosa	On the role of cultural participation in tourism destination performance: an assessment using robust conditional efficiency approach	19 regions and 2 provinces (Italy)	Order-m Method	Accomodation capacity; Tourist arrivals	Tourist bed-nights
2017	Halenur Soysal-Kurt	Measuring tourism efficiency of european countries by using data envelopment analysis	29 European Countries	DEA	Tourism costs; Number of staff; Number of bed places	Tourist receipts; Number of inbound tourists; Number of bed-nights
2018	Amar Oukil, Asma Al-Zidi	Benchmarking the hotel industry in Oman through a three-stage DEA-based procedure	58 Hotels (Oman)	Three-stage DEA	Number of rooms; Number of beds; Number of employees; Employees' salary	Total revenue; Occupancy rate; Number of guests; Number of nights
2019	Spyros Niavis, Dimitrios Tsiotas	Assessing the tourism performance of the Mediterranean coastal destinations: A combined efficiency and effectiveness approach	37 Mediterranean Regions	DEA	Beds capacity; Attractions capacity, Beaches capacity, Labor capacity	Total demand (total overnight stays of tourists in hotels and similar accommodation)
2021	Francisco José Ledesma Rodríguez, Rosa Mª Lorenzo Alegría, Raquel Martín Rivero	A study of hotel sector efficiency in the Canary Islands	Canary Islands	DEA	Labor and capacity (measured by the number of beds)	Overnight stays accounting for different accommodation regimes: only accommodation, accommodation+breakfast, half-board, full-board, and all-inclusive
2021	Vladimir Pavkovic, Goran Jevic, Jelena Jevic, Phong Thanh Nguyen, Cipriana Sava	Determining efficiency of tourism sector in certain european countries and regions by applying DEA analysis	23 European Countries	DEA	Number of hotels and similar accomodation capacities; Number of rooms; Number of bed places	Number of inbound tourists; Number of bed-nights; Tourism expenditure

Agabo-Mateos et al. (2014) used a non-parametric DEA approach and Malmquist indices to evaluate the efficiency and production changes of the Andalusian Public Chain of Youth Hostels (AYH) from 2003 to 2012. The results indicate that the technical efficiency levels of AYH were around 90%, which was better than the Spanish hotel industry during the same period. However, in the latter half of the period studied, pure technical and scale efficiency remained at or near their optimal levels. The years from 2003 to 2008 showed an increase in productive change (14,3%) due to an improvement in efficiency change and a decline in average technical change. During the same years, productivity declined by 21% due to a lack of technological progress and a decrease in efficiency change. The high fixed costs of hostels, which were unaffected by the decline in activity, had a negative impact during the crisis period.

Benito et al. (2014) analyzed the performance of 17 Spanish Autonomous Communities (ACs) from 2002-2010 using DEA and selected variables. They also investigated whether contextual factors affected the efficiency of Spanish tourism regions through bootstrapping the DEA scores with truncated regression using the Simar and Wilson (2007) method. The ACs had an average efficiency score of 0.612 under CRS, meaning that they could improve their output by 38,8%. The average efficiency score under VRS was 0.737 when comparing units with similar behavior and valuing pure technical efficiency. Returns to scale were calculated, indicating that not all regions had the same efficiency. The study showed that Spanish regions were operating at 37,8% below their potential, and there was a slow decline in pure technical efficiency levels, reaching a minimum of 53,6% in 2008 during the economic recession.

Detotto et al. (2014) analyzed the productivity of Italy's hospitality industry, focusing on hotels and restaurants, at the regional level from 2000 to 2004 using non-parametric and parametric methodologies. Their approach combined a window data envelopment analysis (WDEA) with a pooled-truncated and geographical approach to calculate pure technical efficiency. The results showed that Lombardy had the best relative performance, but regional inefficiencies in Italy were significant and mostly stemmed from their inputs. The study highlighted the significance of environmental and hotel quality as productivity-determining factors but also identified several variables such as the underuse of infrastructure and excessive seasonal fluctuations that caused economic inefficiency. The research indicated that Italy lacked effective networking and collaborative marketing tactics, as demonstrated by the absence of spillover effects among Italian areas.

Oliveira et al. (2015) conducted a study to analyze the productivity levels of 28 4 and 5-star accommodations in Portugal's Algarve region that were operational between 2005 and 2007. They used two distinct models, one using variables with units in quantity and the other using variables with monetary units. The study utilized DEA to evaluate the effectiveness of the hotels. The findings revealed that the model using monetary inputs showed better efficiency levels. The study also identified high levels of inefficiency and best practices in the Algarve hotel industry. The factors that affected efficiency were management, inadequate use of infrastructure during the off-season, seasonality, and the institutional and contextual environment..

Ohe and Peypoch (2016) used the WDEA method to study ryokans in the Japanese tourist industry. The study's objectives include locating the industry's best practices and offering management advice to decision-makers. As the data for ryokans are aggregated based on size and region, the WDEA approach is advantageous in this situation because it can handle small data samples, which is crucial. The method has been applied in several other economic sectors, according to the report. According to the study, larger ryokans are more effective than smaller ones, and it advises policymakers to take steps to close 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. The study used the DEA methodology and the Malmquist productivity index to identify external factors that attract tourists. Results showed that 17 Spanish regions operated at 56% of their efficiency potential. Coast, Museum, Mice, Nature, Ski, Food, and Shop were identified as significant tourist attractions. The research stressed the importance of responsible tourism that considers economic, social, and environmental sustainability. Competitive interdependence among all actors in destinations was recommended to achieve sustainable growth.

Oukil et al. (2016) used a two-stage DEA approach to evaluate the effectiveness of 58 hotels in Oman. They found that most of the hotels in Oman are technically inefficient and that star ratings and cultural attractions are the most significant factors in determining efficiency. The study also proposed an empirical method for measuring the allure of tourist locations and identified Muscat as having the most effective hotels due to its concentration of present tourist activities. The study's results provide guidance for future investors and governments to encourage travel to other parts of Oman.

Guccio et al. (2017) investigated the relationship between cultural participation and tourism destination performance, using a robust conditional efficiency method. They found that cultural participation had a positive effect on the efficiency of tourism destinations based on data from Italian regions between 2004 and 2010. The study used a wide range of cultural participation measures and suggested that public cultural policies can enhance the effectiveness of the tourism industry. The researchers recommended that coordination between policies is needed to determine the most beneficial measures for both sectors.

Soysal-Kurt (2017), using DEA, examined the effectiveness of the tourist industries in 29 European nations. Based on fundamental factors influencing the efficiency of the tourist sector, the study revealed that 16 nations were relatively efficient and 13 were relatively inefficient. The study's conclusions offer suggestions for boosting productivity in nations with low productivity, but other aspects should also be considered. The study's contribution is to assess tourist efficiency at the macro level and to offer a general sense of the input/output balance based on specified factors. The number of variables and nations included are constrained, and future research can improve the factors influencing tourist efficiency for a more thorough study.

Oukil and Al-Zidi (2018) used DEA to examine the effectiveness of the hotel sector in Oman and identify environmental factors that affect operational efficiency. Less than 23% of the hotels in the research were judged to be efficient, but the average efficiency score of 83% shows that most hotels handle resources with a respectable level of efficiency. The most significant influences on hotel efficiency were determined to be hotel size, star rating, and cultural attractions. The report recommends more decentralized investment policies that support the growth of the hotel sector outside of the capital and its surrounding areas. For future research, the paper also suggests using expanded DEA models and including more input and output variables.

Niavis and Tsiotas (2019) used DEA to evaluate the efficiency and effectiveness of Mediterranean coastal resorts' tourist performance. The study found significant disparities in how well these destinations function, with improper management being the main cause of inefficiency. The authors suggest that interventions should focus on enhancing areas' relative position in terms of both efficacy and efficiency through diversifying the tourist product, maximizing the value of natural resources, and consistently upskilling key players. The study offers practical advice to decision-makers and has helpful implications for the notion of destination benchmarking.

Rodríguez et al. (2021) analyzed the efficiency of hotel supply in the Canary Islands using data from an official survey of the hotel sector for 2010 and 2015. They used Data Envelopment Analysis (DEA) to estimate technical and scale efficiencies and found that there is potential for improvement in the technological efficiency of hotels in the Canary Islands. Small and large hotels had the highest levels of efficiency, while the highest star-rated hotels had the lowest. Hotels in tourist municipalities had better efficiency than those in island capitals. The study suggests that public policies that encourage hotels to locate in tourist municipalities can improve technical efficiency and competitiveness in the hotel industry.

Pavković et al. (2021) used the DEA method to evaluate the efficiency of the tourism industry in various European countries and regions. The study found that North Macedonia, France, Malta, the Netherlands, Portugal, and Spain showed technical efficiency, while Croatia, Belgium, and Denmark demonstrated total efficiency. On the other hand, transitional nations, Scandinavian, Eastern European, and Mediterranean nations demonstrated comparatively low levels of efficiency. The study stresses the importance of enhancing the efficiency of the tourist industry to maximize its economic benefits. The DEA approach employed in the study is significant as it offers insights into how to develop plans for the maximum efficiency of the tourism sector.

3.5. Chapter Conclusion

In conclusion, efficiency is a complex concept that can be approached from various perspectives, including technical and allocative efficiency. The assessment of efficiency performance is crucial for evaluating business unit performance in relation to strategic goals. Performance evaluation methodologies can be categorized as parametric or non-parametric, stochastic, or deterministic, and efficient frontier or average adjustments. The two primary methodologies for evaluating the efficiency of decision-making units are parametric and non-parametric, with DEA and SFA being the most commonly used models in efficiency evaluation studies. In this chapter, we have discussed the advantages and disadvantages of these two models and their suitability for analyzing the tourism industry. The DEA methodology is favored for assessing the performance of non-profit institutions, including state-provided services, and is also suitable for analyzing the tourism industry. However, it has some drawbacks, including difficulty in formulating statistical hypotheses and evaluating "absolute" efficiency. DEA models can be categorized into two main types: input orientation models and output orientation models, each of which can be further divided into two subcategories: Constant Returns to Scale (CRS)-based models (or CCR) and Variable Returns to Scale (VRS)-based models (or BCC). This chapter provides a comprehensive overview of the concept of efficiency, the methodologies used to assess efficiency, and the DEA model and its variations.

4. Case Study

This chapter will discuss the factors involved in constructing the DEA model for this study. Firstly, in section 4.1., the selection of Portuguese municipalities and the chosen typology of tourist accommodation will be presented. Section 4.2. introduces the model specification and orientation (in subsection 4.2.1.), alongside the selection of input and output variables (in subsection 4.2.2.), and a brief set of descriptive statistics regarding the values of said variables (in subsection 4.2.3.). Finally, in Section 4.3., some conclusions of the chapter are presented.

4.1. Sample and Data Collection

The efficiency analysis of tourist accommodations in certain municipalities is the focus of this dissertation. The initial step in conducting this analysis involves selecting the decision units or DMUs. Thanassoulis (2001) emphasizes that a prerequisite for applying the DEA approach is to ensure homogeneity among the organizations or units being studied. This homogeneity involves organizations that share similar objectives and perform identical tasks. This condition is important to maintain consistency and comparability when using the DEA methodology. In this case, the chosen DMUs are the Portuguese coastal municipalities, where the type of accommodation that will be analyzed is the local housing (in Portuguese, "*alojamento local*").

Based on the criteria established by EUROSTAT, a coastal area is defined as a local administrative unit that satisfies one of two conditions: either it has a maritime border (coastline criterion), or at least 50% of its surface area is within a distance of less than 10 km from the sea (50% surface area criterion) (INE, 2021b). Portugal has 308 municipalities, 278 in the Continent, 19 in the Azores, and 11 in Madeira, with 92 of these being coastal municipalities. Although the goal was to analyze all the coastal areas, due to the lack of data, only 38 municipalities will be studied, which represents 41,3% of the Portuguese coast. These 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.

All the necessary data for selecting inputs and outputs to construct the DEA model was obtained from the INE database. All of the data used is regarding the years 2018, 2019, 2020, and 2021, where the number of local housing in Portugal was 3.534, 3.223, 2.240, and 2.811, respectively (INE, 2022a).

4.2. Model Specification

Using the DEA technique, this study seeks to evaluate and examine the effectiveness of local housing in some Portuguese municipalities. As already mentioned, the two primary models provided by the DEA technique, CCR, and BCC, are well-known and trustworthy for assessing performance through efficiency analysis. The efficiency analysis of this dissertation will be assessed by the BCC model, which is based on VRS technology, a choice made mainly due to the simplicity of the results' reading in the software used, Stata SE.

4.2.1. Orientation

When establishing a DEA model, the orientation chosen is an important factor to consider. As already mentioned in the last chapter, the options are input orientation and output orientation, which focus on minimizing inputs for a given level of outputs and maximizing outputs for a given quantity of inputs, respectively. There are other models which could be used; however, these are not as common as the ones just described.

In this study, it was decided to include both input and output orientations in order to conduct a thorough and comprehensive assessment of each municipality in the sample. This allows us to analyze whether a municipality is more efficient by utilizing inputs to achieve desired outputs or by effectively generating outputs considering the level of inputs. Given the context of accommodation and, more generally, tourism, it is crucial to consider both perspectives as these sectors can be viewed either as public services or profit-driven entities.

4.2.2. Inputs and Outputs

In order to compare the efficiency levels of a municipality, regarding its local housing accommodations, this study selected variables that are commonly used when analyzing the efficiency of such establishments. The choice of these variables aligns with standard practices in the efficiency analysis of tourist establishments, which was studied in the literature review presented in the previous chapter. Alongside this analysis, the availability of data in the INE database was also crucial to the choice of the variables, since some variables presented in the said database couldn't be discriminated by municipalities, didn't present data from the years 2018 to 2021, or didn't have any available data on local housing. In Table 8, the inputs and outputs chosen are presented.

Table 8 – 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

Inputs:

- Accommodation Capacity (Through the Number of Beds): includes the count of beds specifically found in local housing (Agabo-Mateos et al., 2014; Benito et al., 2014; Solana-Ibánez et al., 2016; Oukil et al., 2016; Guccio et al., 2017; Soysal-Kurt, 2017; Oukil & Al-Zidi, 2018; Niavis & Tsiotas, 2019; Rodríguez et al., 2021; Pavković et al., 2021). Data extracted from INE (2022b).
- Number of Accommodations: total number of local housing in each municipality (Pavković et al., 2021). Data extracted from INE (2022a).
- Number of Bedrooms: this variable holds significance due to its representation of a substantial initial investment and its direct impact on generating revenue (Pereira Oliveira et al, 2015; Ohe & Peypoch, 2016; Oukil & Al-Zidi, 2018; Pavković et al., 2021). Data extracted from INE (2022c).

Outputs:

- Total Revenue: represents the overall income generated from multiple sources, including hotel room rentals, revenue from food and beverage sales, earnings from phone call charges, and income from laundry services (Agabo-Mateos et al., 2014; Pereira Oliveira et al, 2015; Ohe & Peypoch, 2016; Oukil & Al-Zidi, 2018). Data extracted from INE (2022d).
- Number of Guests: total count of individuals who stay at least one night in a specific establishment, regardless of the length of their stay (Solana-Ibánez et al., 2016; Oukil et al., 2016; Oukil & Al-Zidi, 2018). Data extracted from INE (2022e).
- Number of Nights Spent: provides a cumulative value of full nights spent in the hotel (Ohe & Peypoch, 2016; Oukil et al., 2016; Oukil & Al-Zidi, 2018; Niavis & Tsiotas, 2019; Rodríguez et al., 2021). Data extracted from INE (2022f).

Given the number of observations in this study (38), it is recommended to analyze a smaller set of inputs and outputs. Banker et al. (1989) proposed a guideline stating that the total number of inputs and outputs should be less than one-third of the number of observations. In this case, the sum of inputs and outputs verifies the rule suggested since 38/3 = 12, (6) which is higher than the total number of variables presented (6, where 3 are inputs and 3 are outputs).

4.2.3. Descriptive Statistics

The descriptive statistics of the inputs and outputs, necessary for the model, are presented in Tables 9, 10, 11, and 12. These tables display the data for the years 2018, 2019, 2020, and 2021 correspondingly.

Table 9 – Descriptive Statistics of 2018

	Mean	Standard Deviation	Minimum	Maximum
Inputs				
Accommodation Capacity	613,5789	639,7617	34	2708
Number of Accommodations	30,18421	48,92181	1	288
Number of Bedrooms	247,8947	247,8926	16	948
Outputs				
Total Revenue (€ in thousands)	2111,211	2707,456	90	9309
Number of Guests	25178,68	31311,15	711	156723
Number of Nights Spent	65841,92	77402,69	2662	291745

Table 10 – Descriptive Statistics of 2019

	Mean	Standard Deviation	Minimum	Maximum
Inputs				
Accommodation Capacity	629,7632	640,6488	41	2669
Number of Accommodations	24,52632	22,5697	3	96
Number of Bedrooms	253,6579	252,6408	20	1064
Outputs				
Total Revenue (€ in thousands)	2431,368	2989,425	90	10488
Number of Guests	27357,87	35306,62	887	177122
Number of Nights Spent	65405,68	78476,04	3407	280952

Table 11 – Descriptive Statistics of 2020

	Mean	Standard Deviation	Minimum	Maximum
Inputs				
Accommodation Capacity	440,7632	450,0665	37	2032
Number of Accommodations	17,68421	15,8815	3	65
Number of Bedrooms	178,7368	177,6489	17	789
Outputs				
Total Revenue (€ in thousands)	862,5789	937,0788	36	3640
Number of Guests	10736,55	15333,84	451	86478
Number of Nights Spent	24414,29	26789,99	1528	114874

Table 12 – Descriptive Statistics of 2021

	Mean	Standard Deviation	Minimum	Maximum
Inputs				
Accommodation Capacity	542,8158	550,5961	43	2552
Number of Accommodations	23	21,08285	3	91
Number of Bedrooms	233,7105	224,9108	20	1047
Outputs				
Total Revenue (€ in thousands)	1567,711	2037,437	111	10072
Number of Guests	15977,97	20686,98	953	112131
Number of Nights Spent	35811,34	38939	3675	157144

4.3. Chapter Conclusions

In summary, this thesis focuses on the efficiency analysis of tourist accommodations in specific coastal municipalities of Portugal, specifically examining the local housing sector. The study ensures homogeneity among the units being studied and considers data from 38 municipalities, representing 41.3% of the Portuguese coast. Using data from 2018 to 2021, the DEA technique with the BCC model is employed to evaluate the efficiency of local housing. The analysis includes inputs such as accommodation capacity, number of accommodations, and number of bedrooms, and outputs such as total revenue, number of guests, and number of nights spent. The study adheres to the guideline of having a limited number of inputs and outputs relative to the number of observations. By conducting this analysis, the study aims to provide valuable insights into the performance of local housing accommodations and contribute to the enhancement of the tourism sector in Portuguese municipalities.

5. Results

This chapter will present all of the results obtained. Firstly, in section 5.1., a brief explanation of the software and the commands used is presented. Section 5.2. introduces the results of the input-oriented model alongside the scaling behaviour of the DMUs (in subsection 5.2.1.) and the peer references (in subsection 5.2.2.). In Section 5.3., it is presented the results regarding the output-oriented model, with, again the scaling behaviour of the DMUs (in subsection 5.3.1.) and peer references (in subsection 5.3.2.). After this, Section 5.4. details the comparison between the results of the two models, while section 5.5. presents the results on the Malmquist Productivity Index. Section 5.6. explains the method used in order to rank the municipalities according to their overall efficiency.

5.1. Software and Data Construction

The outcomes were derived using the Stata SE software. The data for each model were structured in an Excel spreadsheet, where the DMUs were listed in the initial column (such as Caminha, Viana do Castelo, Póvoa do Varzim, etc.), while the subsequent columns contained the input values (in columns 2, 3, and 4) and the output values (in columns 5, 6, and 7). For each Excel spreadsheet imported to Stata, according to the year, the commands used in order to obtain the efficiencies were:

dea accommodation_capacity n_accommodations n_bedrooms = total_revenue n_guests n_nights, rts (vrs) ort (in)

or

dea accommodation_capacity n_accommodations n_bedrooms = total_revenue n_guests n_nights, rts (vrs) ort (out)

The components of these commands are the following:

- accommodation_capacity represents the input “Accommodation Capacity”;
- n_accommodations represents the input “Number of Accommodations”;
- n_bedrooms represents the input “Number of Bedrooms”;
- total_revenue represents the output “Total Revenue”;
- n_guests represents the output “Number of Guests”;
- n_nights represents the output “Number of Nights Spent”;
- rts (vrs) represents the model used, which in this case is the VRS;
- ort (in) / ort (out) represents the orientation used (in-input / out-output).

5.2. Input-Oriented Model

Table 13 displays the efficiency outcomes obtained for the 38 municipalities in the input-oriented model. The first column lists the municipalities, while the second column denotes the years analyzed in this model (2018, 2019, 2020, and 2021). Subsequent columns present the measures of CRS, VRS, and scale efficiency. The last column, labeled returns to scale – RTS –, indicates the scaling behavior of each DMU. The values in this column represent IRS for increasing returns to scale, DRS for decreasing returns to scale, and (-) when the DMU exhibits constant returns to scale.

Table 13 – Efficiency Results of the Input-Oriented Model

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Caminha	2018	71,0%	100,0%	71,0%	irs
	2019	66,1%	69,3%	95,4%	irs
	2020	58,2%	78,3%	74,3%	irs
	2021	46,7%	63,9%	73,1%	irs
Viana do Castelo	2018	100,0%	100,0%	100,0%	-
	2019	92,4%	98,8%	93,5%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Póvoa de Varzim	2018	46,0%	60,7%	75,7%	irs
	2019	54,5%	67,6%	80,7%	irs
	2020	49,9%	55,5%	89,9%	drs
	2021	60,9%	67,7%	90,0%	irs
Alcobaça	2018	35,7%	39,1%	91,3%	irs
	2019	29,9%	36,0%	83,2%	irs
	2020	57,8%	58,0%	99,6%	drs
	2021	62,0%	62,2%	99,8%	irs
Caldas da Rainha	2018	39,8%	42,1%	94,6%	irs
	2019	32,7%	39,4%	83,1%	irs
	2020	30,7%	36,1%	84,9%	irs
	2021	31,0%	46,7%	66,4%	irs
Lourinhã	2018	60,4%	62,3%	97,1%	irs
	2019	57,8%	64,4%	89,7%	irs
	2020	67,7%	67,8%	99,9%	irs
	2021	51,1%	56,5%	90,4%	irs
Óbidos	2018	100,0%	100,0%	100,0%	-
	2019	81,9%	96,2%	85,1%	irs
	2020	44,7%	53,9%	82,9%	irs
	2021	40,1%	59,5%	67,3%	irs
Aveiro	2018	91,6%	91,6%	100,0%	drs
	2019	93,5%	96,5%	97,0%	drs
	2020	63,7%	68,9%	92,4%	drs
	2021	71,4%	89,2%	80,0%	drs
Leiria	2018	61,4%	63,8%	96,2%	irs
	2019	79,4%	81,2%	97,8%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Marinha Grande	2018	38,9%	50,7%	76,8%	irs
	2019	48,3%	100,0%	48,3%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	84,3%	100,0%	84,3%	irs
Pombal	2018	98,7%	100,0%	98,7%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	96,0%	100,0%	96,0%	irs
	2021	52,5%	100,0%	52,5%	irs
Almada	2018	92,6%	92,8%	99,8%	drs
	2019	73,1%	74,1%	98,6%	irs
	2020	55,9%	56,6%	98,8%	drs
	2021	53,9%	54,0%	99,9%	irs
Oeiras	2018	52,9%	100,0%	52,9%	irs
	2019	82,3%	100,0%	82,3%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	73,2%	92,4%	79,2%	irs

Table 13 – Efficiency Results of the Input-Oriented Model (Continuation)

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Setubal	2018	64,9%	68,4%	95,0%	drs
	2019	52,8%	56,3%	93,8%	irs
	2020	46,7%	48,4%	96,5%	drs
	2021	57,1%	57,6%	99,2%	irs
Sintra	2018	100,0%	100,0%	100,0%	-
	2019	100,0%	100,0%	100,0%	-
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Odemira	2018	61,6%	66,1%	93,2%	drs
	2019	65,3%	65,4%	99,8%	irs
	2020	77,1%	90,5%	85,2%	drs
	2021	66,9%	67,8%	98,7%	drs
Santiago do Cacém	2018	69,1%	100,0%	69,1%	irs
	2019	25,2%	34,2%	73,8%	irs
	2020	36,5%	36,5%	99,9%	irs
	2021	39,4%	43,2%	91,1%	irs
Albufeira	2018	79,3%	100,0%	79,3%	drs
	2019	69,7%	100,0%	69,7%	drs
	2020	52,3%	55,6%	94,0%	drs
	2021	95,2%	100,0%	95,2%	drs
Aljezur	2018	65,9%	69,2%	95,3%	drs
	2019	56,7%	58,3%	97,2%	irs
	2020	58,0%	61,8%	93,8%	drs
	2021	51,4%	51,9%	99,1%	drs
Castro Marim	2018	83,6%	95,3%	87,7%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	100,0%	100,0%	100,0%	-
	2021	84,2%	98,9%	85,1%	irs
Faro	2018	100,0%	100,0%	100,0%	-
	2019	100,0%	100,0%	100,0%	-
	2020	89,4%	100,0%	89,4%	drs
	2021	80,4%	80,4%	100,0%	drs
Lagoa	2018	55,1%	56,4%	97,7%	irs
	2019	66,2%	68,7%	96,4%	irs
	2020	63,7%	64,4%	99,0%	drs
	2021	74,6%	75,3%	99,1%	drs
Lagos	2018	98,1%	100,0%	98,1%	drs
	2019	76,1%	100,0%	76,1%	drs
	2020	52,8%	57,2%	92,3%	drs
	2021	70,8%	75,4%	94,0%	drs
Loulé	2018	83,6%	84,8%	98,6%	drs
	2019	75,0%	92,3%	81,3%	drs
	2020	60,7%	69,1%	87,8%	drs
	2021	80,5%	83,1%	96,9%	drs
Olhão	2018	50,9%	52,9%	96,1%	irs
	2019	51,4%	57,1%	90,0%	irs
	2020	50,0%	50,3%	99,6%	drs
	2021	46,5%	46,7%	99,6%	irs
Portimão	2018	100,0%	100,0%	100,0%	-
	2019	85,0%	96,7%	87,9%	drs
	2020	59,7%	66,8%	89,4%	drs
	2021	62,2%	68,6%	90,8%	drs

Table 13 – Efficiency Results of the Input-Oriented Model (Continuation)

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Silves	2018	49,6%	51,1%	97,0%	irs
	2019	46,7%	52,0%	89,8%	irs
	2020	48,4%	48,6%	99,6%	drs
	2021	58,9%	61,1%	96,4%	irs
Tavira	2018	93,7%	98,8%	94,8%	drs
	2019	100,0%	100,0%	100,0%	-
	2020	76,9%	79,0%	97,3%	drs
	2021	86,6%	87,7%	98,7%	drs
Angra do Heroísmo	2018	55,2%	55,2%	100,0%	drs
	2019	48,6%	53,5%	90,8%	irs
	2020	40,5%	41,0%	98,8%	drs
	2021	65,6%	72,1%	91,0%	irs
Horta	2018	47,2%	47,6%	99,2%	irs
	2019	57,4%	60,6%	94,6%	irs
	2020	28,9%	32,3%	89,7%	drs
	2021	58,0%	58,5%	99,2%	irs
Lajes do Pico	2018	35,8%	44,0%	81,4%	irs
	2019	41,5%	56,6%	73,3%	irs
	2020	26,5%	50,0%	52,9%	irs
	2021	43,1%	59,5%	72,4%	irs
Ponta Delgada	2018	79,9%	80,2%	81,4%	drs
	2019	78,7%	79,4%	99,2%	irs
	2020	59,5%	75,9%	78,5%	drs
	2021	59,7%	67,1%	88,9%	drs
Santa Cruz das Flores	2018	70,0%	100,0%	70,0%	irs
	2019	53,5%	100,0%	53,5%	irs
	2020	34,6%	100,0%	34,6%	irs
	2021	56,5%	100,0%	56,5%	irs
Calheta (Madeira)	2018	54,6%	54,6%	99,9%	irs
	2019	43,6%	48,4%	90,2%	irs
	2020	46,0%	49,6%	92,7%	drs
	2021	52,0%	52,0%	99,9%	irs
Porto Santo	2018	26,1%	26,6%	98,1%	irs
	2019	27,9%	46,0%	60,7%	irs
	2020	31,3%	38,0%	82,4%	irs
	2021	38,9%	100,0%	38,9%	irs
Ribeira Brava	2018	51,9%	54,3%	95,5%	irs
	2019	57,3%	100,0%	57,3%	irs
	2020	45,0%	100,0%	45,0%	irs
	2021	76,6%	91,6%	83,6%	irs
Santa Cruz	2018	59,7%	59,8%	99,9%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	45,4%	51,0%	89,0%	irs
	2021	41,6%	43,2%	96,3%	irs
São Vicente	2018	84,2%	84,4%	99,7%	irs
	2019	41,6%	64,7%	64,3%	irs
	2020	26,1%	86,0%	30,4%	irs
	2021	42,8%	61,0%	70,2%	irs

This table displays the values for the three efficiency typologies, Global (CRS), Technical (VRS), and Scale (CRS/VRS), considering the establishments in each municipality, for the years analyzed. On the other hand, Table 14 presents the statistical parameters of the data related to the efficiency of municipalities.

Table 14 – Statistical Parameters from the 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

Regarding Table 14, some conclusions can be withdrawn:

- In CRS efficiency, from the 152 DMUs analyzed, only 20 were concluded to be efficient, meaning that about 86,8% of the sample was considered inefficient, with an efficiency mean of 64,6%;
- In VRS efficiency, 42 DMUs were assumed to be efficient, which meant that approximately 72,4% of all DMUs were concluded to be inefficient, with an efficiency mean of 73,6%;
- In Scale efficiency, again, 20 were considered to be efficient, with 86,8% of the DMUs assumed to be inefficient, but with an efficiency mean of 88,3%.

As already said, regarding CRS efficiency, 20 DMUs were considered to be efficient, with a percentage of 100%. According to Table 13, the results showed that Sintra was the only municipality that presented maximum efficiency throughout the 4 years. Furthermore, Viana do Castelo (2018, 2020, 2021), Óbidos (2018), Marinha Grande (2020), Pombal (2019), Oeiras (2020), Castro Marim (2019, 2020), Faro (2018, 2019), Portimão (2018), and Santa Cruz (2019), presented a CRS efficiency of 100%. The DMUs indicated were also regarded as having VRS and scale efficiency at their maximum.

As for VRS efficiency, it is possible to state that 42 DMUs in the 152 were concluded to be efficient. Pombal, Sintra, and Santa Cruz das Flores, in the years analyzed, all presented maximum efficiency. Alongside these, Caminha (2018), Viana do Castelo (2018, 2020, 2021), Óbidos (2018), Marinha Grande (2019, 2020, 2021), Oeiras (2018, 2019, 2020), Santiago do Cacém (2018), Albufeira (2018, 2019, 2021), Castro Marim (2019, 2020), Faro (2018, 2019, 2020), Lagos (2018, 2019), Portimão (2018), Tavira (2019), Porto Santo (2021), Ribeira Brava (2019, 2020), and Santa Cruz (2019) were the municipalities that presented 100% of VRS efficiency, while all of the remaining DMUs were considered inefficient. According to the statistical parameters given by the model, it can be concluded that, by having an average VRS efficiency score of 73,6%, local housing could achieve the same level of outputs by using 26,4% less inputs.

In the case of scale efficiency, it can be concluded that all DMUs that had 100% CRS efficiency also have the maximum score for scale efficiency. By examining Table 14, it can also be stated that, with an average of 88,3% of scale efficiency, the linear sum of outputs to inputs ratio might be improved by up to 11,7%.

5.2.1. Scaling Behaviour of the DMUs

Table 15 displays the variable returns to scale of the input-oriented model, revealing the behavior of DMUs (decision-making units).

Among the 152 DMUs analyzed, 85 exhibit increasing returns to scale (IRS), 20 have constant returns to scale (CRS), and 47 demonstrate decreasing returns to scale (DRS). The majority of DMUs show IRS, suggesting that 85 of them could enhance their efficiency by increasing the number of input units to achieve optimal scale. On the other hand, the 47 DMUs with DRS should focus on improving their work processes, as an increase in inputs leads to a smaller increase in outputs.

Table 15 – Scaling Behaviour of the Input-Oriented Model

	Variable Returns To Scale		
	IRS	**CRS**	**DRS**
Total	85	20	47

5.2.2. Peers References

Analyzing reference sets is a component of benchmarking actions within the framework of the DEA methodology. To construct virtual efficient DMUs, inefficient DMUs are blended with efficient DMUs from these reference sets, which act as benchmarks.

The analysis was carried out independently for each year, and the DMU, reference sets, and frequencies are detailed in Tables B.22, B.23, B.24, and B.25 (Appendix B). The efficient DMUs that act as peers for technically inefficient DMUs are listed in the reference set column. For technically effective DMUs, the frequency column is filled in with the number of times these DMUs were chosen as peers for less effective DMUs.

In said tables, it can be concluded that Sintra is the only DMU used as a peer reference throughout the 4 years analyzed, which can be explained due to the fact that is the only municipality with 100% efficiency in all the years. The frequencies of this DMU are 13, 27, 14, and 15, in 2018, 2019, 2020, and 2021, respectively. Even though it is the municipality with the higher frequency in 2019, this does not apply to the other years. In 2018, with a frequency of 28, Óbidos was the most used as a peer reference. In 2020, it was Oeiras, with a frequency of 19 and, in 2021, it was Leiria, with a frequency of 33. Faro was also a DMU presented as a reference through the years 2018, 2019, and 2020, but not in 2021, since it was considered inefficient.

Some other peculiar cases must be addressed:

- Alcobaça (2020) and Olhão (2020) were the DMUs that presented the higher number of peer references, each with a total of 5. Alcobaça had Viana do Castelo (0,484825), Leiria (0,0645852), Marinha Grande (0,428171), Oeiras (0,0114545), and Sintra (0,0109645) has its references. Leiria (1,40e-07), Marinha Grande (0,266847), Oeiras (0,239612), Sintra (0,0799726), and Castro Marim (0,413568) were the references of Olhão.
- Albufeira (2018, 2019), Lagos (2018), Castro Marim (2019), Santa Cruz das Flores (2020), and Ribeira Brava (2020) are all efficient DMUs but don’t serve as peer references for the inefficient ones.
- The DMUs Caminha (2018), Marinha Grande (2019, 2021), Pombal (2018, 2020, 2021), Oeiras (2018, 2019), Santiago do Cacém (2018), Santa Cruz das Flores (2018, 2019, 2021), Ribeira Brava (2019), and Porto Santo (2021) exhibit technical efficiencies at the maximum score, of 100%. However, these municipalities present peer references, which could mean that there is still potential for some improvement.

5.3. Output-Oriented Model

Table 16 displays the efficiency outcomes obtained for the 38 municipalities in the output-oriented model. The first column lists the municipalities, while the second column denotes the years analyzed in this model (2018, 2019, 2020, and 2021). Subsequent columns present the measures of CRS, VRS, and scale efficiency. The last column, labeled returns to scale – RTS –, indicates the scaling behavior of each DMU.

Table 16 – Efficiency Results of the Output-Oriented Model

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Caminha	2018	68,5%	69,7%	98,2%	irs
	2019	66,1%	68,2%	96,9%	irs
	2020	58,2%	66,5%	87,5%	irs
	2021	46,7%	48,4%	96,5%	irs
Viana do Castelo	2018	100,0%	100,0%	100,0%	-
	2019	92,4%	98,6%	93,7%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Póvoa de Varzim	2018	46,0%	48,4%	94,9%	irs
	2019	54,5%	61,2%	89,1%	irs
	2020	49,9%	59,4%	83,9%	drs
	2021	60,9%	63,0%	96,7%	irs
Alcobaça	2018	35,7%	35,9%	99,3%	irs
	2019	29,9%	30,9%	97,0%	irs
	2020	57,8%	61,8%	93,6%	irs
	2021	62,0%	62,6%	99,1%	irs
Caldas da Rainha	2018	39,8%	40,1%	99,1%	irs
	2019	32,7%	34,1%	96,0%	irs
	2020	30,7%	32,4%	94,5%	irs
	2021	31,0%	31,2%	99,3%	irs
Lourinhã	2018	60,4%	60,6%	99,8%	irs
	2019	57,8%	61,2%	94,5%	irs
	2020	67,7%	68,2%	99,2%	drs
	2021	51,1%	53,0%	96,3%	irs
Óbidos	2018	100,0%	100,0%	100,0%	-
	2019	81,9%	95,2%	85,9%	irs
	2020	44,7%	44,8%	99,7%	irs
	2021	40,1%	46,1%	87,0%	irs
Aveiro	2018	91,7%	100,0%	91,7%	drs
	2019	93,5%	96,6%	96,8%	irs
	2020	63,7%	71,5%	89,1%	drs
	2021	71,4%	91,1%	78,3%	drs
Leiria	2018	61,4%	62,3%	98,6%	irs
	2019	79,4%	80,5%	98,6%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Marinha Grande	2018	38,9%	39,0%	99,8%	irs
	2019	48,3%	52,5%	92,0%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	84,3%	100,0%	84,3%	irs
Pombal	2018	98,7%	100,0%	98,7%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	96,0%	100,0%	96,0%	irs
	2021	52,5%	52,5%	100,0%	-
Almada	2018	92,6%	92,8%	99,8%	drs
	2019	73,1%	73,6%	99,3%	irs
	2020	55,9%	57,2%	97,7%	irs
	2021	53,9%	55,2%	97,6%	irs
Oeiras	2018	52,9%	53,7%	98,5%	irs
	2019	82,3%	100,0%	82,3%	irs
	2020	100,0%	100,0%	100,0%	-
	2021	73,2%	85,9%	85,2%	irs

Table 16 – Efficiency Results of the Output-Oriented Model (Continuation)

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Setubal	2018	64,9%	69,3%	93,6%	drs
	2019	52,8%	54,1%	97,6%	irs
	2020	46,7%	50,5%	92,5%	drs
	2021	57,1%	57,3%	99,8%	irs
Sintra	2018	100,0%	100,0%	100,0%	-
	2019	100,0%	100,0%	100,0%	-
	2020	100,0%	100,0%	100,0%	-
	2021	100,0%	100,0%	100,0%	-
Odemira	2018	61,6%	66,7%	92,4%	drs
	2019	65,3%	65,4%	99,8%	irs
	2020	77,1%	91,1%	84,6%	drs
	2021	66,9%	68,1%	98,3%	irs
Santiago do Cacém	2018	69,1%	100,0%	69,1%	irs
	2019	25,2%	26,9%	93,7%	irs
	2020	36,5%	39,5%	92,3%	drs
	2021	39,4%	39,6%	99,4%	irs
Albufeira	2018	79,3%	100,0%	79,3%	drs
	2019	69,7%	100,0%	69,7%	drs
	2020	52,3%	86,6%	60,4%	drs
	2021	95,2%	100,0%	95,2%	drs
Aljezur	2018	65,9%	69,9%	94,4%	drs
	2019	56,7%	56,7%	99,9%	irs
	2020	58,0%	64,8%	89,6%	irs
	2021	51,4%	52,5%	97,8%	irs
Castro Marim	2018	83,6%	94,4%	88,5%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	100,0%	100,0%	100,0%	-
	2021	84,2%	98,2%	85,7%	irs
Faro	2018	100,0%	100,0%	100,0%	-
	2019	100,0%	100,0%	100,0%	-
	2020	89,4%	100,0%	89,4%	drs
	2021	80,4%	80,4%	99,9%	irs
Lagoa	2018	55,1%	56,4%	97,7%	irs
	2019	66,2%	67,1%	98,7%	irs
	2020	63,7%	67,3%	94,7%	drs
	2021	74,6%	75,9%	98,3%	drs
Lagos	2018	98,1%	100,0%	98,1%	drs
	2019	76,1%	100,0%	76,1%	drs
	2020	52,8%	66,0%	80,0%	drs
	2021	70,8%	78,1%	90,7%	drs
Loulé	2018	83,6%	84,9%	98,5%	drs
	2019	75,0%	94,8%	79,2%	irs
	2020	60,7%	70,8%	85,6%	drs
	2021	80,5%	83,2%	96,7%	drs
Olhão	2018	50,9%	51,1%	99,5%	irs
	2019	51,4%	53,1%	96,7%	irs
	2020	50,0%	50,5%	99,0%	irs
	2021	46,5%	47,9%	97,1%	irs
Portimão	2018	100,0%	100,0%	100,0%	-
	2019	85,0%	97,8%	86,9%	drs
	2020	59,7%	68,2%	87,6%	drs
	2021	62,2%	70,3%	88,5%	drs

Table 16 – Efficiency Results of the Output-Oriented Model (Continuation)

Municipality	Year	Efficiency			RTS
		CRS	VRS	Scale	
Silves	2018	49,6%	50,0%	99,2%	irs
	2019	46,7%	47,8%	97,7%	irs
	2020	48,4%	49,2%	98,2%	irs
	2021	58,9%	59,1%	99,7%	irs
Tavira	2018	93,7%	98,9%	94,7%	drs
	2019	100,0%	100,0%	100,0%	-
	2020	76,9%	80,7%	95,4%	drs
	2021	86,6%	88,0%	98,4%	drs
Angra do Heroísmo	2018	55,2%	55,3%	99,8%	drs
	2019	48,6%	50,6%	95,9%	irs
	2020	40,5%	47,2%	85,7%	drs
	2021	65,6%	68,0%	96,5%	irs
Horta	2018	47,2%	47,3%	99,9%	drs
	2019	57,4%	58,9%	97,4%	irs
	2020	28,9%	37,1%	77,9%	drs
	2021	58,0%	65,0%	89,3%	irs
Lajes do Pico	2018	35,8%	36,7%	97,6%	irs
	2019	41,5%	48,5%	85,6%	irs
	2020	26,5%	28,9%	91,6%	irs
	2021	43,1%	49,0%	87,8%	irs
Ponta Delgada	2018	79,9%	80,2%	99,6%	drs
	2019	78,7%	79,0%	99,7%	irs
	2020	59,5%	77,4%	77,0%	drs
	2021	59,7%	69,1%	86,4%	drs
Santa Cruz das Flores	2018	70,0%	100,0%	70,0%	irs
	2019	53,5%	100,0%	53,5%	irs
	2020	34,6%	35,1%	98,7%	irs
	2021	56,5%	100,0%	56,5%	irs
Calheta (Madeira)	2018	54,6%	59,5%	91,7%	irs
	2019	43,6%	45,4%	96,1%	irs
	2020	46,0%	52,6%	87,3%	drs
	2021	52,0%	52,9%	98,1%	irs
Porto Santo	2018	26,1%	26,1%	99,8%	irs
	2019	27,9%	31,1%	89,6%	irs
	2020	31,3%	33,1%	94,6%	irs
	2021	38,9%	39,7%	98,0%	irs
Ribeira Brava	2018	51,9%	52,3%	99,3%	irs
	2019	57,3%	100,0%	57,3%	irs
	2020	45,0%	45,3%	99,4%	irs
	2021	76,6%	89,2%	85,9%	irs
Santa Cruz	2018	59,7%	59,8%	100,0%	irs
	2019	100,0%	100,0%	100,0%	-
	2020	45,4%	46,6%	97,5%	irs
	2021	41,6%	47,3%	87,9%	irs
São Vicente	2018	84,2%	84,4%	99,8%	irs
	2019	41,6%	50,0%	83,2%	irs
	2020	26,1%	26,1%	100,0%	-
	2021	42,8%	49,7%	86,1%	irs

As already mentioned in the input-oriented model, this table displays the values for the three efficiency typologies, Global (CRS), Technical (VRS), and Scale (CRS/VRS). Table 17, however, presents the statistical parameters of the data related to the efficiency of municipalities.

Table 17 – Statistical Parameters from the 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

Regarding Table 17, some conclusions can be withdrawn:

- In CRS efficiency, from the 152 DMUs analyzed, only 20 were concluded to be efficient, meaning that about 86,8% of the sample was considered inefficient, with an efficiency mean of 64,6%;
- In VRS efficiency, 36 DMUs were assumed to be efficient, which meant that approximately 76,3% of all DMUs were concluded to be inefficient, with an efficiency mean of 69,9%;
- In Scale efficiency, 22 were considered to be efficient, with 85,5% of the DMUs assumed to be inefficient, but with an efficiency mean of 93,1%.

As already said, regarding CRS efficiency, 20 DMUs were considered to be efficient, with a percentage of 100%. According to Table 16, the results showed that Sintra was the only municipality that presented maximum efficiency throughout the 4 years. Furthermore, Viana do Castelo (2018, 2020, 2021), Óbidos (2018), Leiria (2020, 2021), Marinha Grande (2020), Pombal (2019), Oeiras (2020), Castro Marim (2019, 2020), Faro (2018, 2019), Portimão (2018), Tavira (2019), and Santa Cruz (2019) presented a CRS efficiency of 100%. The DMUs indicated were also regarded as having VRS and scale efficiency at their maximum.

As for VRS efficiency, it is possible to state that 36 DMUs were concluded to be efficient. In this case, only Sintra presented maximum efficiency for all years. Alongside this, Viana do Castelo (2018, 2020, 2021), Óbidos (2018), Aveiro (2018), Leiria (2020, 2021), Marinha Grande (2020, 2021), Pombal (2018, 2019, 2020), Oeiras (2019, 2020), Santiago do Cacém (2018), Albufeira

(2018, 2019, 2021), Castro Marim (2019, 2020), Faro (2018, 2019, 2020), Lagos (2018, 2019), Portimão (2018), Tavira (2019), Santa Cruz das Flores (2018, 2019, 2021), Ribeira Brava (2019), and Santa Cruz (2019) were the municipalities that presented 100% of VRS efficiency, while all of the remaining DMUs were considered inefficient. According to the statistical parameters given by the model, it can be concluded that, by having an average VRS efficiency score of 69,9%, local housing could achieve the same level of outputs by using 30,1% less inputs.

In the case of scale efficiency, it can be concluded that 22% of the DMUs have the maximum score for scale efficiency. By examining Table 17, it can also be stated that, with an average of 93,1% of scale efficiency, the linear sum of outputs to inputs ratio might be improved by up to 6,9%.

5.3.1. Scaling Behaviour of the DMUs

Table 18 displays the variable returns to scale of the output-oriented model, revealing the behavior of DMUs (decision-making units).

Among the 152 DMUs analyzed, 90 exhibit increasing returns to scale (IRS), 22 have constant returns to scale (CRS), and 40 demonstrate decreasing returns to scale (DRS). The majority of DMUs show IRS, suggesting that 90 of them could enhance their efficiency by increasing the number of output units to achieve optimal scale. However, the 40 DMUs with DRS might increase their efficiency if they start using fewer inputs.

Table 18 – Scaling Behaviour of the Output-Oriented Model

	Variable Returns To Scale		
	IRS	**CRS**	**DRS**
Total	90	22	40

5.3.2. Peer References

Tables C.26, C.27, C.28, and C.29 (Appendix C) present the peer references for the municipalities studied. This analysis was carried out independently for each year, with the DMU, reference sets, and frequencies. The efficient DMUs that act as peers for technically inefficient DMUs are listed in the reference set column. For technically effective DMUs, the frequency column is filled in with the number of times these DMUs were chosen as peers for less effective DMUs.

In said tables, it can be concluded that, again, Sintra is the only DMU used as a peer reference throughout the 4 years analyzed, which can be explained due to the fact that is still the only municipality with 100% efficiency in all the years, just like in the input-oriented model. The frequencies of this DMU in this model are 22, 26, 28, and 22, in 2018, 2019, 2020, and 2021, respectively. Even though it is the municipality with the higher frequency in 2019 and in 2020, this does not apply to the other years. In 2018, with a frequency of 27, Óbidos was the most used as a peer reference, and, in 2021, it was Leiria, with a frequency of 31.

Some other peculiar cases must be addressed:

- In this model, the highest number of peer references that a DMU has is 3. As seen in the tables, various DMUs confirm this, such as Alcobaça (2018), Caldas da Rainha (2018), Lourinhã (2018), Aveiro (2018), Almada (2018, 2021), Loulé (2018), Olhão (2018, 2021), Póvoa do Varzim (2020), and Porto Santo (2020).
- Albufeira (2018), and Castro Marim (2019) are both efficient DMUs but don't serve as peer references for the inefficient ones.
- The DMUs Viana do Castelo (2018, 2020, 2021), Aveiro (2018), Marinha Grande (2020, 2021), Pombal (2018, 2020), Oeiras (2019), Santiago do Cacém (2018), Albufeira (2019), Castro Marim (2020), Faro (2020), Lagos (2018, 2019), Tavira (2019), Santa Cruz das Flores (2018, 2019, 2021), Ribeira Brava (2019), and Santa Cruz (2019) exhibit technical efficiencies at the maximum score, of 100%. However, these municipalities present peer references, which could mean that there is still potential for some improvement.

5.4. Comparative Analysis and Ranking of Municipalities

VRS Efficiency Results and Model Comparison

The VRS efficiency results shown in Figure 7 are average values based on the models that were produced by each municipality between the years 2018, 2019, 2020, and 2021. The graph demonstrates that, among the three periods of 50%–60%, 80%–90%, and 90%–100%, the input-oriented model exhibits the highest frequency of findings (8). The output-oriented model, on the other hand, mostly shows outcomes (9) between 50% and 60%. It is noteworthy that the output-oriented model only recognizes Sintra as being technically efficient, but the input-oriented model considers the municipalities of Pombal, Sintra, and Santa Cruz das Flores to be technically efficient. The output-oriented model has a lower average VRS efficiency of 69.9% compared to the input-oriented model's average VRS efficiency of 73.6%.

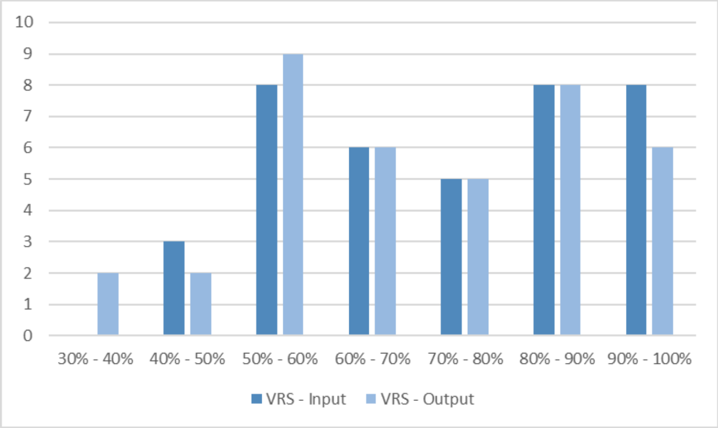

Figure 7 - Results of the VRS Efficiency Comparison Between the Two Models

CRS Efficiency Results and Model Comparison

Figure 8 displays the average CRS efficiencies obtained by each municipality. The highest frequency of results for the input-oriented model is observed in the 50%-60% and 60%-70% ranges, totaling 8 municipalities in each. Conversely, the output-oriented model shows the most results (9 municipalities) in the 50%-60% range. A comparison between Figures 7 and 8 reveals a wider distribution of CRS efficiencies across different ranges of results. Sintra is the only municipality considered efficient in both models for all analyzed years. The average CRS efficiency for both models is 64.6%.

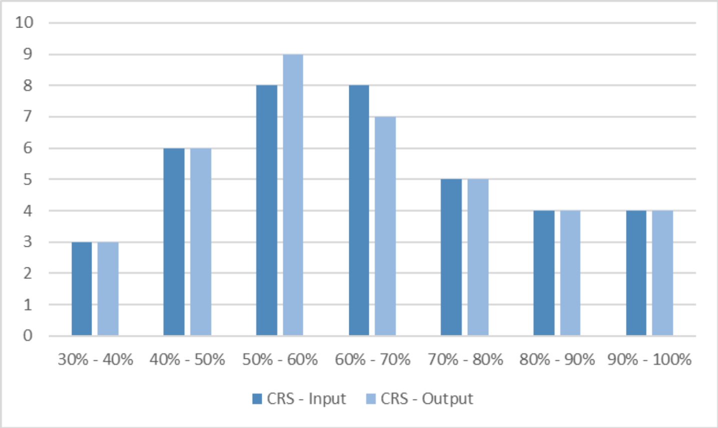

Figure 8 - Results of the CRS Efficiency Comparison Between the Two Models

Scaling Behaviour and Model Comparison

Figure 9 displays the percentages of the scaling behaviour. In the input-oriented model, approximately 55.9% of DMUs display increasing returns to scale (IRS) behaviour, while the output-oriented model has 59.2% of its DMUs exhibiting this behaviour. For constant returns to scale (CRS) behaviour, 13.2% and 14.5% of DMUs demonstrate this pattern in the input and output-oriented models, respectively. In terms of decreasing returns to scale (DRS) behaviour, the input-oriented model has 30.9% of DMUs showing this pattern, while the output-oriented model has 26.3%.

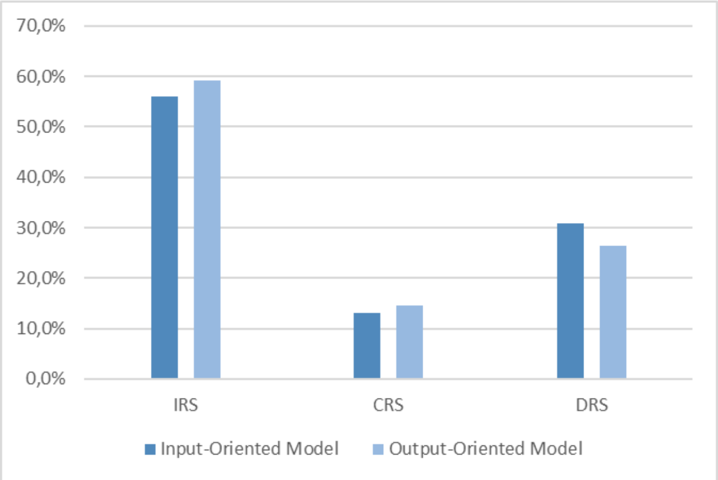

Figure 9 - Results of the Scaling Behaviour Comparison Between the Two Models

Peer References and Model Comparison

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 10, 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.

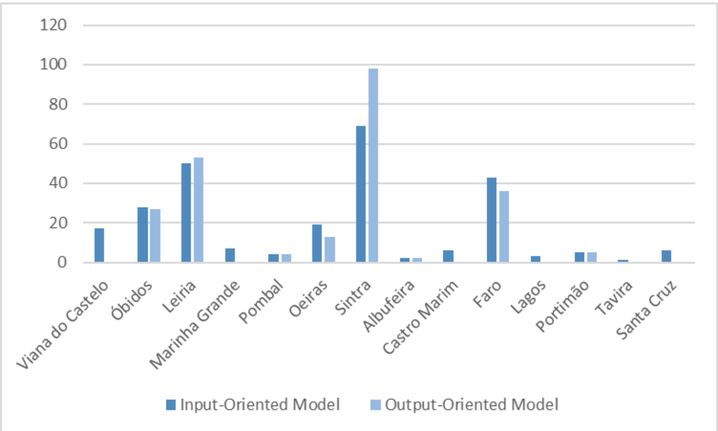

Figure 10 – Results of Peer References Comparison Between the Two Models

5.5. Malmquist Productivity Index

The Malmquist index, which was covered in section 3.3, compares an entity's performance over time to that of reference technologies to determine how productive it has become. It is feasible to assess relative changes in productivity and establish whether gains are brought on by advances in technology, increases in technical efficiency, or a mix of both by breaking down the Malmquist index into sub-indices.

The Malmquist indices for the 38 municipalities, in the 4 years analyzed, including productivity indices, differences in technical efficiency, and technological advancements, are presented in Appendix D, specifically Table D.30. Also, in same Appendix, it exists Table D.31, with the mean values of the MPI according to the municipalities.

According to Table D.30, the average annual productivity experienced a decrease of 1,7% based on the values derived from the Malmquist Index. The overall performance improvement of the entity was driven by positive contributions in terms of technical change, resulting in a 2,4% efficiency improvement. However, there was a decline of 5,3% in efficiency related to technological change. These results may be explained due to the COVID-19 pandemic since it affected mainly the two last years of the sample which was used to conduct this dissertation.

Based on the results from Table D.31, it can be concluded that out of the 38 municipalities evaluated, 22 experienced productivity losses. Among the remaining 16 municipalities that had productivity gains, all of them showed improvements in technical change, while only one municipality showed gains in technological change.

Upon analyzing the Total Factor Productivity Change (TFPCH), it can be observed that only one municipality (Lourinhã) experienced productivity losses consistently across all the years. In terms of technical efficiency (TECH), three municipalities (Caminha, Óbidos, and Almada) demonstrated losses, even though there were three municipalities (Leiria, Sintra, and Porto Santo) that presented only results equal to or above 1. For technological change (TECCH) every municipality had at least one period that presented gains and one that had losses.

The graph in Figure 11 shows the average values obtained for the period 2018-2019, indicating a decrease in total productivity of 4.4%. This decline can be attributed to a 1.3% decrease in technical efficiency and a 3.5% decrease in technological progress. Between 2019-2020, the loss in technical efficiency was relatively small, accounting for only 5.4% of the overall decline in total productivity, which amounted to 37.6%. These significant losses can be attributed to the impact of the pandemic. However, between 2020 and 2021, there was a remarkable reversal of this trend, with a substantial increase in technical efficiency (13.8%) and technological change (21.1%). Notably, 2021 witnessed a strong growth in tourism, leading to a 36.9% increase in total productivity, indicating a return to normal values across all variables.

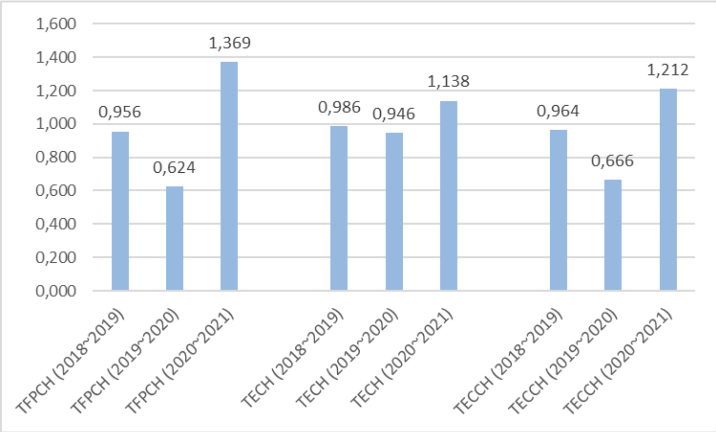

Figure 11 - Mean Values of TFPCH, TECH, and TECCH.

Looking back to Table D.31, the overall results will be examined. Considering the 4-year average, Óbidos had the poorest performance in both TFPCH and TECCH, experiencing losses of 29.0% and 24.6% respectively, while Portimão had the worst performance in TECCH, with losses of 13.7%. On the other hand, Horta achieved the best performance in TFPCH, with a gain of 30.6%. Marinha Grande had the highest improvement in TECH, gaining 38.4%, and, lastly, Pombal showed the most significant improvement in TECCH, with a gain of 3.45%.

5.6. Ranking of the Municipalities

This research study aimed to develop a systematic methodology for ranking the municipalities under investigation according to their efficiency levels. Several authors have proposed various ranking methods for DEA models, including Wu (2011), Martín et al. (2017), Aristovnik et al. (2013), Foroughi and Tamiz (2005), Jahanshahloo et al. (2007), Toloo et al. (2009), Tsou and Huang (2010), among others. To ensure simplicity, the ranking method employed in this study is based on Aristovnik et al.'s (2013) approach.

The geometric mean of the VRS efficiencies across multiple years Is used to determine an overall efficiency score for each municipality. Table 19 illustrates this method for the years 2018, 2019, 2020, and 2021, showcasing the changes in rankings over time. The table includes the DMUs in the first column, the geometric mean of the input and output-oriented models' results for each year in the second, fourth, sixth, and eighth columns, and the corresponding rankings in the third, fifth, seventh, and ninth columns.

Table 19 – Ranking of the Municipalities by Year

DMU	2018		2019		2020		2021	
	VRS Efficiency	Ranking	VRS Efficiency	Ranking	VRS Efficiency	Ranking	VRS Efficiency	Ranking
Caminha	83,5%	17	68,7%	21	72,2%	12	55,6%	27
Viana do Castelo	100,0%	1	98,7%	12	100,0%	1	100,0%	1
Póvoa de Varzim	54,2%	29	64,3%	24	57,4%	24	65,3%	21
Alcobaça	37,5%	37	33,3%	37	59,8%	22	62,4%	23
Caldas da Rainha	41,1%	35	36,6%	36	34,2%	38	38,2%	38
Lourinhã	61,4%	24	62,8%	25	68,0%	16	54,7%	29
Óbidos	100,0%	1	95,7%	15	49,2%	29	52,4%	33
Aveiro	95,7%	12	96,5%	14	70,2%	13	90,1%	9
Leiria	63,1%	23	80,8%	17	100,0%	1	100,0%	1
Marinha Grande	44,5%	34	72,5%	20	100,0%	1	100,0%	1
Pombal	100,0%	1	100,0%	1	100,0%	1	72,5%	16
Almada	92,8%	14	73,8%	19	56,9%	25	54,6%	30
Oeiras	73,3%	19	100,0%	1	100,0%	1	89,1%	10
Setubal	68,9%	21	55,2%	29	49,4%	28	57,4%	26
Sintra	100,0%	1	100,0%	1	100,0%	1	100,0%	1
Odemira	66,4%	22	65,4%	23	90,8%	9	67,9%	20
Santiago do Cacém	100,0%	1	30,3%	38	38,0%	35	41,4%	37
Albufeira	100,0%	1	100,0%	1	69,4%	15	100,0%	1
Aljezur	69,5%	20	57,5%	27	63,3%	20	52,2%	34
Castro Marim	94,8%	13	100,0%	1	100,0%	1	98,6%	7
Faro	100,0%	1	100,0%	1	100,0%	1	80,4%	13
Lagoa	56,4%	27	67,9%	22	65,8%	19	75,6%	15
Lagos	100,0%	1	100,0%	1	61,5%	21	76,7%	14
Loulé	84,8%	15	93,6%	16	70,0%	14	83,1%	12
Olhão	52,0%	31	55,1%	30	50,4%	27	47,3%	35
Portimão	100,0%	1	97,3%	13	67,5%	17	69,4%	18
Silves	50,5%	32	49,9%	33	48,9%	30	60,1%	25
Tavira	98,9%	11	100,0%	1	79,8%	10	87,8%	11
Angra do Heroísmo	55,3%	28	52,0%	32	44,0%	33	70,0%	17
Horta	47,4%	33	59,7%	26	34,6%	37	61,7%	24
Lajes do Pico	40,2%	36	52,4%	31	38,0%	34	54,0%	31
Ponta Delgada	80,2%	18	79,2%	18	76,6%	11	68,1%	19
Santa Cruz das Flores	100,0%	1	100,0%	1	59,3%	23	100,0%	1
Calheta (Madeira)	57,0%	26	46,9%	34	51,1%	26	52,5%	32
Porto Santo	26,4%	38	37,8%	35	35,4%	36	63,0%	22
Ribeira Brava	53,3%	30	100,0%	1	67,3%	18	90,4%	8
Santa Cruz	59,8%	25	100,0%	1	48,7%	31	45,2%	36
São Vicente	84,4%	16	56,9%	28	47,4%	32	55,1%	28

There are several notable observations to be made regarding this table:

- Sintra, represented by the green color, consistently ranked first every year without any changes in both the ranking position and efficiency score.
- The yellow-highlighted DMUs achieved a first-place ranking in almost every year except for one, indicating their consistently high performance.
- The DMUs highlighted in burnt orange did not experience significant changes in their rankings from year to year, with a difference of no more than 5 spots. Additionally, these DMUs maintained a relatively narrow range of rankings, with no more than an 8-spot difference between their highest and lowest rankings over the four-year period.

In Table 20, a final ranking is assigned to the municipalities based on the same method used in the previous table. However, in this case, the analysis does not differentiate the results by year but instead provides an overall assessment. The aim is to determine the municipalities' final rankings by considering their efficiency scores across all the years analyzed. By aggregating the results and conducting a comprehensive analysis, a final ranking is established to evaluate the municipalities' performance without year-specific distinctions.

Table 20 – Final Ranking of the Municipalities

DMU	VRS Efficiency	Final Ranking	DMU	VRS Efficiency	Final Ranking
Sintra	100,0%	1	Caminha	69,3%	20
Viana do Castelo	99,7%	2	Almada	67,9%	21
Castro Marim	98,3%	3	Lagoa	66,1%	22
Faro	94,7%	4	Lourinhã	61,5%	23
Pombal	92,3%	5	Aljezur	60,3%	24
Albufeira	91,3%	6	Santa Cruz	60,2%	25
Tavira	91,2%	7	Póvoa de Varzim	60,1%	26
Oeiras	89,9%	8	São Vicente	59,5%	27
Santa Cruz das Flores	87,7%	9	Setubal	57,3%	28
Aveiro	87,4%	10	Angra do Heroísmo	54,6%	29
Leiria	84,5%	11	Silves	52,2%	30
Lagos	82,9%	12	Calheta (Madeira)	51,7%	31
Loulé	82,4%	13	Olhão	51,1%	32
Portimão	82,2%	14	Horta	49,6%	33
Ponta Delgada	75,9%	15	Santiago do Cacém	46,7%	34
Ribeira Brava	75,5%	16	Alcobaça	46,5%	35
Marinha Grande	75,3%	17	Lajes do Pico	45,6%	36
Odemira	71,9%	18	Porto Santo	38,6%	37
Óbidos	70,5%	19	Caldas da Rainha	37,4%	38

All of the conclusions that need to be drawn from this chapter will be further explained, in the following chapter.

6. Conclusions

This final chapter will be divided into four sections. The first one, section 6.1., presents a summary of this dissertation, alongside some overall results. Section 6.2. discusses some conclusive thoughts about the given results. Section 6.3. presents the limitations of this work while section 6.3. discussed some possible future work.

6.1. Summary

In summary, this research study analyzed the efficiency of 38 Portuguese coastal municipalities with local housing over a 4-year period (2018-2021). The focus was on assessing the efficiency of these municipalities in terms of their housing sector.

In this research, various methodologies available for performance evaluation were evaluated, considering their advantages and disadvantages. After a thorough analysis, it was made the decision to employ the non-parametric method called Data Envelopment Analysis (DEA) with an efficient frontier approach. DEA is a widely used performance evaluation technique in studies with similar scopes. DEA is based on mathematical programming and aims to determine the relative efficiency of entities or decision-making units (DMUs) that consume inputs and produce outputs. It allows for the evaluation of multiple inputs and outputs simultaneously. The efficiency measurement model in DEA can be oriented towards inputs or outputs. The input orientation focuses on minimizing inputs while keeping outputs constant, aiming to identify the most efficient utilization of resources. On the other hand, the output orientation aims to maximize outputs while keeping inputs constant, emphasizing the production efficiency of the DMUs. In this particular study, it was applied both input and output orientations to measure efficiency. This decision enables a comprehensive evaluation of the performance of the entities under investigation. By utilizing both orientations, areas where inputs can be minimized, or outputs can be maximized to improve efficiency can be identified.

The selection of variables for the accommodation sector inputs and outputs played a crucial role in the results obtained in this study. After conducting a thorough literature review and considering the available information, three inputs and three outputs were identified. Inputs included the accommodation capacity, the number of accommodations, and the number of bedrooms. Outputs, on the other hand, comprised the total revenue, the number of guests, and the number of nights spent. These variables were chosen to attempt to accurately capture the efficiency and performance of local housing in Portugal in the research analysis.

After finalizing the model, the subsequent stage involved its implementation and determination to calculate the efficiency values for each municipality. Of all 38 municipalities analyzed in this study, only one obtained the maximum value of efficiency throughout the 4 years considered, which was Sintra. This was the result for both the input and the output-oriented models. In terms of average efficiencies, when considering an input orientation, the average CRS efficiency was 64,6%, the average VRS efficiency was 73,6%, and the average scale efficiency was 88,3%. However, when adopting an output orientation, the corresponding values were 64,6%, 69,9%, and 93,1% for CRS, VRS, and scale efficiencies, respectively.

Regarding the input-oriented model, the analysis of efficiency in the housing sector revealed that the majority of municipalities were considered inefficient. Only a small percentage of DMUs exhibited high-efficiency levels in terms of CRS, VRS, and scale efficiency. Sintra stood out as the only municipality consistently efficient throughout the four years. Other municipalities achieved maximum efficiency in specific years. Returns to scale analysis indicated that most DMUs could benefit from increasing input units to improve efficiency. The analysis of reference sets highlighted Sintra as the most frequent peer reference, but other municipalities were also chosen as benchmarks in different years.

The analysis using the output-oriented model examined efficiency in terms of CRS, VRS, and scale efficiency among 152 DMUs. Only 20 DMUs were found to be efficient in CRS efficiency, with Sintra consistently achieving maximum efficiency. VRS efficiency analysis identified 36 efficient DMUs, with Sintra maintaining maximum efficiency and other municipalities showing 100% efficiency in specific years. Scale efficiency assessment revealed 22 efficient DMUs, with Sintra and all DMUs with 100% CRS efficiency achieving maximum scale efficiency. Sintra was consistently chosen as a peer reference due to its 100% efficiency, with Óbidos having the highest frequency in 2018 and Leiria in 2021. Some DMUs had up to three peer references. Certain DMUs achieved perfect technical efficiency scores of 100%, but still had peer references, indicating potential for further improvement.

The analysis using the Malmquist index examined productivity changes in 38 municipalities over four years. The overall average annual productivity decreased by 1.7%, primarily due to a decline in technological change, resulting in a 5.3% decrease in efficiency. However, there were positive contributions from technical change, leading to a 2.4% improvement in efficiency. The COVID-19 pandemic had a significant impact on the results, particularly in the later years of the study. Among the municipalities evaluated, 22 experienced productivity losses, while 16 showed gains in technical change, and only one showed gains in technological change.

Finally, a systematic methodology for ranking municipalities based on efficiency was developed. The approach calculated the overall efficiency score by using the geometric mean of VRS efficiencies across multiple years. Sintra consistently ranked first, while some municipalities consistently performed well, and others maintained stable rankings. A final ranking was assigned by considering efficiency scores across all years, providing an overall assessment of performance without year-specific distinctions, where Sintra came first with an overall efficiency of 100%, in second came Viana do Castelo with an efficiency of 99,7% and, in third stands Castro Marim, with an overall efficiency of 98,3%.

6.2. Conclusive Thoughts

Some conclusive thoughts about the results are presented:

- The research study evaluates the efficiency of Portuguese coastal municipalities in the housing sector using DEA. The results indicate that the majority of municipalities were inefficient in terms of their housing sector performance. This emphasizes the need for improving resource utilization and output levels in order to enhance efficiency.
- Considering the inefficiency observed in the majority of municipalities, it is essential for local authorities and housing sector stakeholders to identify areas that need improvement. Measures should be taken to optimize resource utilization and maximize output levels. Benchmarking against efficient municipalities, such as Sintra, Óbidos, Leiria, and others, can offer valuable insights and serve as a guide for implementing strategies to enhance efficiency in the accommodation sector.
- The analysis showed that increasing returns to scale were common among municipalities, indicating that scaling up housing capacity and optimizing resource allocation can enhance efficiency. Strategies aimed at increasing scale efficiency have the potential to contribute to an overall improvement in the sector.
- The research study revealed a decline in overall average annual productivity, mainly attributed to a decrease in technological change. The COVID-19 pandemic had a significant impact on the results, particularly in the later years of the study. It is essential to recognize the influence of external factors like pandemics and adjust their strategies accordingly. Adapting strategies can help mitigate productivity losses and improve efficiency in the housing sector.
- The research study established a systematic methodology for ranking municipalities based on efficiency, providing a comprehensive assessment of their performance. Sintra consistently ranked first, showcasing outstanding performance in the accommodation sector. This position may be explained due to the rich tourism culture that Sintra has. Not only it offers the typical coastal tourism, such as all of the remaining municipalities, but it also gains the majority of its tourists due to large amounts of monuments, pastries, and historical sightseeing. Other municipalities, such as Viana do Castelo and Castro Marim, also demonstrated high levels of efficiency, and should be acknowledged. Viana do Castelo has also a vast number of museums, cathedrals, and palaces, and, above hall, a privileged view of the river Lima, which could also explain the high score of efficiency. Castro Marim's score may derive from the low amount of local housing in the municipality, making it easier to reach a higher spot in the rankingnof efficiency.

The findings of this research study emphasize the need for strategic management interventions and continuous improvement initiatives in the local housing of these municipalities.

The local authorities, such as the mayors, should be focusing on optimizing resource utilization, adopting best practices from benchmark municipalities, and adapting to changing technological landscapes. Collaboration and knowledge sharing among municipalities can facilitate the implementation of efficient accommodations policies and contribute to overall sectoral improvement.

6.3. Limitations

Upon the completion of this research work, it is essential to highlight its limitations to prevent misinterpretations. It is crucial to present these limitations to ensure that no erroneous conclusions are drawn, or decisions made without a solid foundation.

Firstly, throughout the course of this work, the title was not reiterated, which could lead to misinterpretations regarding the goal of this dissertation. The analysis of exogenous variables was not conducted due to a shift in the work's objective.

Secondly, it is mandatory to understand that the efficiency values obtained in this study are dependent on the specific variables selected as inputs and outputs for the DEA model. It is important to acknowledge that any alteration in these variables could result in significantly different outcomes compared to the findings presented in this research.

Thirdly, the research work focuses on a limited sample of 38 coastal municipalities due to data availability constraints. To provide a more comprehensive and robust analysis, it would be beneficial to include data from all Portuguese coastal municipalities. Additionally, it is important to acknowledge that the study may not account for all local housing within each municipality, which may impact the overall findings.

Fourthly, the research study did not conduct a super-efficiency analysis or implement methods to address the influence of potential outliers that could distort the efficiency results. Considering the size and population differences among municipalities would have been beneficial to account for these variables, as they can impact the sample and overall findings.

Fifthly, the period of years used to conduct this analysis is not the most accurate in order to understand the real efficiency of the accommodations. Due to the pandemic, the tourism sector was highly damaged and so was the hospitality sector. This can be seen in some of the results presented.

Finally, it's significant to remember that DEA assesses the relative efficiency of the municipalities. Thus, the municipalities deemed as efficient should continue to strive for even greater efficiency in their operations than become complacent.

6.4. Future Work

This research work holds relevance in the field of performance evaluation of tourist accommodation in municipalities, particularly in the context of Portuguese coastal areas, between the years 2018 and 2021. While there have been previous studies conducted on the performance evaluation of tourist accommodation, this study stands out as it specifically focuses on local accommodation in Portuguese coastal municipalities. The timeframe of the study allows an analysis of the performance trends and changes over a four-year period. By narrowing the scope to this specific context, the study provides unique insights and contributes to the existing body of literature in this area.

It is advised that more research is done in this area to increase the reliability and sturdiness of the results that have been provided. Studies employing alternative methodologies, such as stochastic frontier models (SFA), as well as similar studies using the DEA approach, may be helpful in order to gain a distinct perspective from the one presented in this study. Also, methods, like order-m, could also be advantageous in order to study and evaluate the impact of external variables in this sector. This extra research would allow comparisons to be made between present work and future efforts. The analysis would also substantially benefit from investigating other approaches and adding various input and output variables, which would add supplementary insights to the findings.

Lastly, it would be beneficial to address the issue of outliers by conducting a future efficiency analysis, as already mentioned in the limitations of this work. By excluding potential outliers from the sample, it would be possible to evaluate their impact on the efficiency results of the remaining units under analysis. This additional test would provide valuable insights into the influence of outliers on the overall efficiency assessment.

References

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

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

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

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

Banker, R., Charnes, A., & Cooper, W. (1989). An introduction to data envelopment analysis with some of its models and their uses. Management. Scicience, 30, 1078–1092.

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

Barros, C. P., & Athanassiou, M. (2004). Efficiency in European seaports with DEA: Evidence from Greece and Portugal. *Maritime Economics and Logistics*, *6*(2), 122–140. https://doi.org/10.1057/palgrave.mel.9100099

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

Burkart, A., & Medlik, S. (1974). Tourism: Past, Present and Future. (2nd ed.). Heinemann.

Cambridge University Press. (2013). Tourism. (4th ed.). Cambridge Advanced Learner's Dictionary. Cambridge. https://dictionary.cambridge.org/dictionary/english/tourism

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

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

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

Chen, C. F. (2007). Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan. *Tourism Management*, *28*(3), 696–702. https://doi.org/10.1016/j.tourman.2006.04.023

Chen, L.-F., Hsiao, C.-H., & Tsai, C.-F. (2010). Three-stage-DEA model selections and managerial decision. *African Journal of Business Management*, *4*(14), 3046–3055. https://academicjournals.org/journal/AJBM/article-full-text-pdf/FA89D2625490

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

Cook, W. D., & Zhu, J. (2005). Modeling performance measurement: Applications and implementation issues in DEA. In *Modeling Performance Measurement: Applications and Implementation Issues in DEA*. Springer US. https://doi.org/10.1007/b104529

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Handbook on Data Envelopment Analysis, Second Edition. In *Handbook on Data Envelopment Analysis, Second Edition* (Vol. 164).

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

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

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

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

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*.

Eurostat. (2023, January 5). Nights spent at tourist accommodation establishments by country/world region of residence of the tourist. https://ec.europa.eu/eurostat/web/products-datasets/-/tin00176

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

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

Foroughi, A. A., & Tamiz, M. (2005). An effective total ranking model for a ranked voting system. Omega, 33(6), 491–496. https://doi.org/10.1016/j.omega.2004.07.013

Førsund, F. R. (2018, March 1). Economic interpretations of DEA. *Socio-Economic Planning Sciences*. Elsevier Ltd. https://doi.org/10.1016/j.seps.2017.03.004

Goeldner, C. R., & Ritchie, J. R. B. (2003). Tourism: Principles, Practices, and Philosophies. In *John Wiley & Sons, Inc., Hoboken, New Jersey*. https://www.entornoturistico.com/wp-content/uploads/2018/04/Tourism-Principles-Practices-Philosophies.pdf

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

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

Hsieh, L. F., & Lin, L. H. (2010). A performance evaluation model for international tourist hotels in Taiwan-An application of the relational network DEA. *International Journal of Hospitality Management*, *29*(1), 14–24. https://doi.org/10.1016/j.ijhm.2009.04.004

Hubbell, L. L. (2007). Quality, efficiency, and accountability: Definitions and applications. *New Directions for Higher Education*, *2007*(140), 5–13. https://doi.org/10.1002/he.276

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

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

INE. (2021b). *Tourism Statistics 2021*. https://www.ine.pt/ngt_server/attachfileu.jsp?look_parentBoui=567576412&att_display=n&att_download=y

INE. (2022a). *Estabelecimentos de alojamento turístico (N.º) por Localização geográfica (NUTS - 2013) e Tipo (alojamento turístico); Anual* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009873&contexto=bd&selTab=tab2

INE. (2022b). *Capacidade de alojamento (N.º) nos estabelecimentos de alojamento turístico por Localização geográfica (NUTS - 2013) e Grau de urbanização; Anual.* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009184&contexto=bd&selTab=tab2

INE. (2022c). *Quartos (N.º) em estabelecimentos de alojamento turístico por Localização geográfica (NUTS - 2013) e Tipo (alojamento turístico); Anual.* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009874&contexto=bd&selTab=tab2

INE. (2022d). *Proveitos totais (€) nos estabelecimentos de alojamento turístico por Localização geográfica (NUTS - 2013) e Tipo (alojamento turístico); Anual.* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009878&contexto=bd&selTab=tab2

INE. (2022e). *Hóspedes (N.º) nos estabelecimentos de alojamento turístico por Localização geográfica (NUTS - 2013) e Local de residência (País - lista reduzida); Anual.* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009930&contexto=bd&selTab=tab2

INE. (2022f). *Dormidas (N.º) nos estabelecimentos de alojamento turístico por Localização geográfica (NUTS - 2013) e Local de residência (País); Anual.* https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_indicadores&indOcorrCod=0009182&contexto=bd&selTab=tab2

INE. (2023). *Tourist activity continues to reach record highs – February 2023*. https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_destaques&DESTAQUESdest_boui=590405096&DESTAQUESmodo=2

Jahanshahloo, G. R., Junior, H. V., Lotfi, F. H., & Akbarian, D. (2007). A new DEA ranking system based on changing the reference set. European Journal of Operational Research, 181(1), 331–337. https://doi.org/10.1016/j.ejor.2006.06.012

Jaini, N., Anuar, A. N. A., & Daim, M. S. (2012). The practice of sustainable tourism in ecotourism sites among ecotourism providers. *Asian Social Science*, *8*(4), 175–179. https://doi.org/10.5539/ass.v8n4p175

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

Kuah, C. T., & Wong, K. Y. (2011). Efficiency assessment of universities through data envelopment analysis. *Procedia Computer Science*, *3*, 499–506. https://doi.org/10.1016/j.procs.2010.12.084

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

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

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

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

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

Martín, J. C., Mendoza, C., & Román, C. (2017). A DEA Travel–Tourism Competitiveness Index. Social Indicators Research, 130(3), 937–957. https://doi.org/10.1007/s11205-015-1211-3

Mouzas, S. (2006). Efficiency versus effectiveness in business networks. *Journal of Business Research*, 59(10-11), 1124-1132. https://doi.org/10.1016/j.jbusres.2006.09.018

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

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

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

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

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

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

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

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

Porcelli, F. (2009). Measurement of Technical Efficiency. A brief survey on parametric and non-parametric techniques. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.232.4843&rep=rep1&type=pdf

Portal Diplomático. (n.d.). Sobre Portugal. https://portaldiplomatico.mne.gov.pt/sobre-portugal

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*.

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

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

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

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

Statista. (2023, February 2). Number of international tourist arrivals worldwide 1950-2022. https://www.statista.com/statistics/209334/total-number-of-international-tourist-arrivals/

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/

Thanassoulis, E. (2000). DEA and its use in the regulation of water companies. *European Journal of Operational Research*, *127*(1), 1–13. https://doi.org/10.1016/S0377-2217(99)00436-1

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

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

Toloo, M., Sohrabi, B., & Nalchigar, S. (2009). A new method for ranking discovered rules from data mining by DEA. Expert Systems with Applications, 36(4), 8503–8508. https://doi.org/10.1016/j.eswa.2008.10.038

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

Tsou, C. M., & Huang, D. Y. (2010). On some methods for performance ranking and correspondence analysis in the DEA context. European Journal of Operational Research, 203(3), 771–783. https://doi.org/10.1016/j.ejor.2009.09.010

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

Turismo de Portugal (2017). *Estratégia Turismo 2027 (ET2027).* https://www.turismodeportugal.pt/pt/Turismo_Portugal/Estrategia/Estrategia_2027/Paginas/default.aspx

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

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

Wu, W. W. (2011). Beyond Travel & Tourism competitiveness ranking using DEA, GST, ANN and Borda count. *Expert Systems with Applications*, *38*(10), 12974–12982. https://doi.org/10.1016/j.eswa.2011.04.096

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

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

Appendix

Appendix A – Tourism

Table A.21 – Definitions of Tourism

Authors	Definition
Hunziker and Kraph as cited in Burkart and Medlik (1974:40)	"The sum of the phenomena and relationships arising from the travel and stay of non-residents, in so far as they do not lead to permanent residence and are not connected to any earning activity"
Jafari (1977:8) as cited in Leiper (1974)	"Tourism is the study of man away from his usual habitat, of the industry which responds to his needs, and of the impacts that both he and the industry have on the host's socio-cultural, economic and physical environments"
Ansett Arlines (1977:773) as cited in Leiper (1974)	"Tourism refers to the provision of transportation, accommodation, recreation, food, and related services for domestic and overseas travelers. It involves travel for all purposes, including recreation and business ...."
McIntosh (1977: ix) as cited in Leiper (1974)	"Tourism can be defined as the science, art, and business of attracting and transporting visitors, accommodating them and graciously catering to their needs and wants"
Australian Department of Tourism & Recreation (1975:2) as cited in Leiper (1974)	"Tourism is an identifiable nationally important industry. The industry involves a wide cross-section of component activities including the provision of transportation, accommodation, recreation, food, and related services"
Leiper (1974)	"It is the system involving the discretionary travel and temporary stay of persons away from their usual place of residence for one or more nights, excepting tours made for the primary purpose of earning remuneration from points en route"
Cambridge University Press (2013)	"The business of providing services such as transport, places to stay, or entertainment for people who are on holiday"
United Nations World Tourism Organization (2000) as cited in Gonap (2018)	"Tourism is a social, cultural and economic phenomenon which entails the movement of people to countries or places outside their usual environment for personal or business/professional purposes"
Gonap (2018)	"Tourism is a multi-faceted phenomenon which involves movement to and stay in destinations outside the normal place of residence for the purpose of recreation, business, education, health, etc."

Ryan (1991:5) as cited in Tribe (1997)	"A study of the demand for and supply of accommodation and supportive services for those staying away from home, and the resultant patterns of expenditure, income creation, and employment"
McIntosh and Goeldner (1995:10) as cited in Tribe (1997)	"Tourism may be defined as the sum of the phenomena and relationships arising from the interaction of tourists, business suppliers, host governments, and host communities in the process of attracting and hosting these tourists and other visitors"
Tribe (1997)	"Tourism is essentially an activity engaged in by human beings and the minimum necessary features that need to exist for it to be said to have occurred include the act of travel from one place to another, a particular set of motives for engaging in that travel (excluding commuting for work), and the engagement in activity at the destination"
Wahab (1977:26) as cited in Panosso Netto (2009)	"A human intentional activity that serves as a means of communication and as a link of interaction between the peoples, inside a country or even beyond its geographical demarcations. It involves the temporary displacement of people from one region to another, country or even continent, with the objective of satisfying necessities and not the realization of remunerated activity"
Cooper et al. (1993:4) as cited in Panosso Netto (2009)	"Tourism can be thought of as a whole range of individuals, businesses, organizations, and places that combine in some way to deliver a travel experience. Tourism is a multidimensional, multifaceted activity which touches many lives and many different economic activities"
Panosso Netto (2009)	"Tourism is the phenomenon caused by the departure and return of human beings from their place of habitual residence, for reasons that can be revealed or concealed. It presupposes hospital encounters and communication with other people, and companies that offer services and technology so that the act of coming and going is possible. It generates sensorial and psychological experiences as well as positive and negative effects on the economic, political, environmental, and socio-cultural environments"

Appendix B – Peer References of Input-Oriented Model

Table B.22 – Peer References of the Input-Oriented Model in 2018

DMU	Peer References	Frequency
Caminha	Faro; Portimão	-
Viana do Castelo		2
Póvoa de Varzim	Óbidos	-
Alcobaça	Óbidos; Faro	-
Caldas da Rainha	Óbidos; Faro	-
Lourinhã	Óbidos; Faro	-
Óbidos		28
Aveiro	Óbidos; Sintra; Faro	-
Leiria	Óbidos; Faro	-
Marinha Grande	Óbidos; Faro	-
Pombal	Faro; Portimão	-
Almada	Óbidos; Sintra; Faro	-
Oeiras	Óbidos	-
Setubal	Óbidos; Sintra	-
Sintra		13
Odemira	Óbidos; Sintra	-
Santiago do Cacém	Faro; Portimão	-
Albufeira		0
Aljezur	Viana do Castelo; Óbidos; Sintra	-
Castro Marim	Óbidos; Faro	-
Faro		17
Lagoa	Óbidos	-
Lagos		0
Loulé	Óbidos; Sintra; Faro	-
Olhão	Óbidos; Faro	-
Portimão		5
Silves	Óbidos; Faro	-
Tavira	Viana do Castelo; Óbidos; Sintra	-
Angra do Heroísmo	Óbidos; Sintra; Faro	-
Horta	Óbidos; Sintra; Faro	-
Lajes do Pico	Óbidos	-
Ponta Delgada	Óbidos; Sintra; Faro	-
Santa Cruz das Flores	Óbidos	-
Calheta (Madeira)	Óbidos; Sintra	-
Porto Santo	Óbidos	-
Ribeira Brava	Óbidos	-
Santa Cruz	Óbidos; Sintra	-
São Vicente	Óbidos; Sintra	-

Table B.23 – Peer References of the Input-Oriented Model in 2019

DMU	Peer References	Frequency
Caminha	Pombal; Sintra; Faro	-
Viana do Castelo	Sintra; Santa Cruz	-
Póvoa de Varzim	Sintra; Faro	-
Alcobaça	Sintra; Faro	-
Caldas da Rainha	Sintra; Faro	-
Lourinhã	Sintra; Santa Cruz	-
Óbidos	Sintra; Faro	-
Aveiro	Pombal; Sintra; Faro	-
Leiria	Pombal; Faro	-
Marinha Grande	Sintra	-
Pombal		4
Almada	Sintra; Faro	-
Oeiras	Sintra; Faro	-
Setubal	Sintra; Faro	-
Sintra		27
Odemira	Sintra; Faro; Tavira; Santa Cruz	-
Santiago do Cacém	Sintra	-
Albufeira		0
Aljezur	Sintra; Faro; Santa Cruz	-
Castro Marim		0
Faro		23
Lagoa	Sintra; Faro; Santa Cruz	-
Lagos		3
Loulé	Sintra; Faro; Lagos	-
Olhão	Pombal; Faro	-
Portimão	Faro; Lagos	-
Silves	Faro; Santa Cruz	-
Tavira		1
Angra do Heroísmo	Sintra; Faro	-
Horta	Sintra	-
Lajes do Pico	Sintra	-
Ponta Delgada	Sintra; Faro	-
Santa Cruz das Flores	Sintra	-
Calheta (Madeira)	Sintra	-
Porto Santo	Sintra; Faro	-
Ribeira Brava	Sintra; Faro	-
Santa Cruz		6
São Vicente	Sintra; Faro	-

Table B.24 – Peer References of the Input-Oriented Model in 2020

DMU	Peer References	Frequency
Caminha	Leiria; Oeiras	-
Viana do Castelo		12
Póvoa de Varzim	Oeiras; Castro Marim	-
Alcobaça	Viana do Castelo; Leiria; Marinha Grande; Oeiras; Sintra	-
Caldas da Rainha	Leiria; Oeiras	-
Lourinhã	Viana do Castelo; Leiria; Marinha Grande	-
Óbidos	Oeiras	-
Aveiro	Leiria; Sintra; Castro Marim	-
Leiria		17
Marinha Grande		7
Pombal	Leiria	-
Almada	Viana do Castelo; Oeiras; Sintra	-
Oeiras		19
Setubal	Viana do Castelo; Oeiras; Sintra	-
Sintra		14
Odemira	Viana do Castelo; Leiria; Sintra	-
Santiago do Cacém	Viana do Castelo; Oeiras	-
Albufeira	Leiria; Marinha Grande; Sintra	-
Aljezur	Viana do Castelo; Oeiras; Sintra	-
Castro Marim		6
Faro		3
Lagoa	Viana do Castelo; Leiria; Oeiras	-
Lagos	Viana do Castelo; Sintra	-
Loulé	Viana do Castelo; Leiria; Sintra	-
Olhão	Leiria; Marinha Grande; Oeiras; Sintra; Castro Marim	-
Portimão	Marinha Grande; Sintra	-
Silves	Marinha Grande; Oeiras; Sintra; Castro Marim	-
Tavira	Viana do Castelo; Leiria; Sintra	-
Angra do Heroísmo	Oeiras; Castro Marim; Faro	-
Horta	Leiria; Oeiras; Faro	-
Lajes do Pico	Oeiras	-
Ponta Delgada	Leiria; Sintra; Faro	-
Santa Cruz das Flores		0
Calheta (Madeira)	Viana do Castelo; Leiria; Oeiras	-
Porto Santo	Leiria; Oeiras	-
Ribeira Brava		0
Santa Cruz	Leiria	-
São Vicente	Oeiras	-

Table B.25 – Peer References of the Input-Oriented Model in 2021

DMU	Peer References	Frequency
Caminha	Leiria	-
Viana do Castelo		3
Póvoa de Varzim	Leiria	-
Alcobaça	Leiria; Sintra	-
Caldas da Rainha	Leiria	-
Lourinhã	Leiria	-
Óbidos	Leiria	-
Aveiro	Leiria; Sintra	-
Leiria		33
Marinha Grande	Leiria	-
Pombal	Leiria	-
Almada	Leiria; Sintra	-
Oeiras	Leiria	-
Setubal	Leiria; Sintra	-
Sintra		15
Odemira	Viana do Castelo; Leiria; Sintra	-
Santiago do Cacém	Leiria	-
Albufeira		2
Aljezur	Viana do Castelo; Leiria; Sintra	-
Castro Marim	Leiria	-
Faro	Viana do Castelo; Sintra	-
Lagoa	Leiria; Sintra	-
Lagos	Leiria; Sintra; Albufeira	-
Loulé	Leiria; Sintra	-
Olhão	Leiria; Sintra	-
Portimão	Leiria; Sintra; Albufeira	-
Silves	Leiria; Sintra	-
Tavira	Leiria; Sintra	-
Angra do Heroísmo	Leiria	-
Horta	Leiria	-
Lajes do Pico	Leiria	-
Ponta Delgada	Leiria; Sintra	-
Santa Cruz das Flores	Leiria	-
Calheta (Madeira)	Leiria	-
Porto Santo	Leiria	-
Ribeira Brava	Leiria	-
Santa Cruz	Leiria	-
São Vicente	Leiria	-

Appendix C – Peer References of Output-Oriented Model

Table C.26 – Peer References of the Output-Oriented Model in 2018

DMU	Peer References	Frequency
Caminha	Faro; Portimão	-
Viana do Castelo	Óbidos; Sintra	-
Póvoa de Varzim	Óbidos	-
Alcobaça	Óbidos; Sintra; Faro	-
Caldas da Rainha	Óbidos; Sintra; Faro	-
Lourinhã	Óbidos; Sintra; Faro	-
Óbidos		27
Aveiro	Óbidos; Sintra; Faro	-
Leiria	Óbidos; Faro	-
Marinha Grande	Óbidos; Faro	-
Pombal	Faro; Portimão	-
Almada	Óbidos; Sintra; Faro	-
Oeiras	Óbidos	-
Setubal	Óbidos; Sintra	-
Sintra		22
Odemira	Óbidos; Sintra	-
Santiago do Cacém	Faro; Portimão	-
Albufeira		0
Aljezur	Óbidos; Sintra	-
Castro Marim	Óbidos; Faro	-
Faro		14
Lagoa	Óbidos; Sintra	-
Lagos	Sintra; Portimão	-
Loulé	Sintra; Faro; Portimão	-
Olhão	Óbidos; Sintra; Faro	-
Portimão		5
Silves	Óbidos; Faro	-
Tavira	Óbidos; Sintra	-
Angra do Heroísmo	Óbidos; Sintra	-
Horta	Óbidos; Sintra	-
Lajes do Pico	Óbidos	-
Ponta Delgada	Óbidos; Sintra	-
Santa Cruz das Flores	Óbidos	-
Calheta (Madeira)	Sintra	-
Porto Santo	Óbidos; Sintra	-
Ribeira Brava	Óbidos; Sintra	-
Santa Cruz	Óbidos; Sintra	-
São Vicente	Óbidos; Sintra	-

Table C.27 – Peer References of the Output-Oriented Model in 2019

DMU	Peer References	Frequency
Caminha	Pombal; Faro	-
Viana do Castelo	Sintra	-
Póvoa de Varzim	Sintra; Faro	-
Alcobaça	Sintra; Faro	-
Caldas da Rainha	Sintra; Faro	-
Lourinhã	Sintra	-
Óbidos	Sintra; Faro	-
Aveiro	Pombal; Faro	-
Leiria	Pombal; Faro	-
Marinha Grande	Sintra	-
Pombal		4
Almada	Sintra; Faro	-
Oeiras	Sintra; Faro	-
Setubal	Sintra; Faro	-
Sintra		26
Odemira	Sintra; Faro	-
Santiago do Cacém	Sintra	-
Albufeira	Sintra	-
Aljezur	Sintra; Faro	-
Castro Marim		0
Faro		22
Lagoa	Sintra	-
Lagos	Sintra	-
Loulé	Sintra; Faro	-
Olhão	Pombal; Faro	-
Portimão	Sintra; Faro	-
Silves	Faro	-
Tavira	Sintra	-
Angra do Heroísmo	Sintra; Faro	-
Horta	Sintra	-
Lajes do Pico	Sintra	-
Ponta Delgada	Sintra; Faro	-
Santa Cruz das Flores	Sintra	-
Calheta (Madeira)	Sintra	-
Porto Santo	Sintra; Faro	-
Ribeira Brava	Sintra; Faro	-
Santa Cruz	Faro	-
São Vicente	Sintra; Faro	-

Table C.28 – Peer References of the Output-Oriented Model in 2020

DMU	Peer References	Frequency
Caminha	Leiria; Oeiras	-
Viana do Castelo	Oeiras; Sintra	-
Póvoa de Varzim	Leiria; Oeiras; Sintra	-
Alcobaça	Sintra	-
Caldas da Rainha	Leiria; Sintra	-
Lourinhã	Leiria; Sintra	-
Óbidos	Oeiras; Sintra	-
Aveiro	Leiria; Sintra	-
Leiria		22
Marinha Grande	Sintra	
Pombal	Leiria	-
Almada	Oeiras; Sintra	-
Oeiras		13
Setubal	Oeiras; Sintra	-
Sintra		28
Odemira	Leiria; Sintra	-
Santiago do Cacém	Leiria; Sintra	-
Albufeira	Sintra	-
Aljezur	Oeiras; Sintra	-
Castro Marim	Leiria; Sintra	-
Faro	Leiria; Sintra	-
Lagoa	Leiria; Sintra	-
Lagos	Sintra	-
Loulé	Leiria; Sintra	-
Olhão	Sintra	-
Portimão	Leiria; Sintra	-
Silves	Sintra	-
Tavira	Leiria; Sintra	-
Angra do Heroísmo	Leiria; Oeiras	-
Horta	Leiria; Sintra	-
Lajes do Pico	Leiria; Oeiras	-
Ponta Delgada	Leiria; Sintra	-
Santa Cruz das Flores	Oeiras	-
Calheta (Madeira)	Leiria; Sintra	-
Porto Santo	Leiria; Oeiras; Sintra	-
Ribeira Brava	Leiria; Oeiras	-
Santa Cruz	Leiria; Sintra	-
São Vicente	Oeiras	-

Table C.29 – Peer References of the Output-Oriented Model in 2021

DMU	Peer References	Frequency
Caminha	Leiria	-
Viana do Castelo	Sintra	-
Póvoa de Varzim	Leiria	-
Alcobaça	Leiria; Sintra	-
Caldas da Rainha	Leiria; Sintra	-
Lourinhã	Leiria; Sintra	-
Óbidos	Leiria	-
Aveiro	Leiria; Sintra	-
Leiria		31
Marinha Grande	Leiria	-
Pombal	Leiria	-
Almada	Leiria; Sintra; Albufeira	-
Oeiras	Leiria	-
Setubal	Sintra	-
Sintra		22
Odemira	Leiria; Sintra	-
Santiago do Cacém	Leiria; Sintra	-
Albufeira		2
Aljezur	Leiria; Sintra	-
Castro Marim	Leiria	-
Faro	Sintra	-
Lagoa	Leiria; Sintra	-
Lagos	Sintra	-
Loulé	Leiria; Sintra	-
Olhão	Leiria; Sintra; Albufeira	-
Portimão	Leiria; Sintra	-
Silves	Leiria; Sintra	-
Tavira	Leiria; Sintra	-
Angra do Heroísmo	Leiria	-
Horta	Leiria; Sintra	-
Lajes do Pico	Leiria	-
Ponta Delgada	Leiria; Sintra	-
Santa Cruz das Flores	Leiria	-
Calheta (Madeira)	Leiria; Sintra	-
Porto Santo	Leiria	-
Ribeira Brava	Leiria	-
Santa Cruz	Leiria; Sintra	-
São Vicente	Leiria	-

Appendix D – Malmquist Productivity Index

Table D.30 - Malmquist Productivity Indexes

Dmu	Year	Total Factor Productivity Index (TFPCH)	Technical Change (TECH)	Technological Change (TECCH)
Caminha	2018~2019	0,9586	0,9647	0,9937
	2019~2020	0,6867	0,8802	0,7801
	2020~2021	1,0592	0,8034	1,3184
Viana do Castelo	2018~2019	0,876	0,9237	0,9483
	2019~2020	0,6887	1,0826	0,6362
	2020~2021	1,2082	1	1,2082
Póvoa de Varzim	2018~2019	1,2379	1,1868	1,0431
	2019~2020	0,6247	0,9144	0,6832
	2020~2021	1,3086	1,2218	1,071
Alcobaça	2018~2019	0,781	0,8386	0,9313
	2019~2020	1,1498	1,9304	0,5956
	2020~2021	1,2823	1,0739	1,1941
Caldas da Rainha	2018~2019	0,7713	0,8221	0,9382
	2019~2020	0,7234	0,9372	0,772
	2020~2021	1,2726	1,012	1,2575
Lourinhã	2018~2019	0,9999	0,9567	1,0451
	2019~2020	0,6757	1,1711	0,577
	2020~2021	0,9658	0,7539	1,2811
Óbidos	2018~2019	0,707	0,8185	0,8637
	2019~2020	0,3383	0,546	0,6197
	2020~2021	1,0841	0,8965	1,2093
Aveiro	2018~2019	0,924	1,0206	0,9053
	2019~2020	0,5028	0,6807	0,7386
	2020~2021	1,4494	1,121	1,2929
Leiria	2018~2019	1,0846	1,2925	0,8391
	2019~2020	0,9649	1,2597	0,766
	2020~2021	1,3159	1	1,3159
Marinha Grande	2018~2019	1,2279	1,2402	0,9901
	2019~2020	1,2654	2,0704	0,6112
	2020~2021	0,9234	0,8425	1,096
Pombal	2018~2019	1,0794	1,0128	1,0658
	2019~2020	0,7493	0,9601	0,7804
	2020~2021	0,6882	0,5473	1,2573
Almada	2018~2019	0,7666	0,7891	0,9715
	2019~2020	0,4599	0,765	0,6012
	2020~2021	1,2585	0,9642	1,3053
Oeiras	2018~2019	1,5841	1,5553	1,0185
	2019~2020	0,8431	1,2154	0,6937
	2020~2021	0,8409	0,7318	1,1491

Table D.30 - Malmquist Productivity Indexes (Continuation)

Dmu	Year	Total Factor Productivity Index (TFPCH)	Technical Change (TECH)	Technological Change (TECCH)
Oeiras	2018~2019	1,5841	1,5553	1,0185
	2019~2020	0,8431	1,2154	0,6937
	2020~2021	0,8409	0,7318	1,1491
Setubal	2018~2019	0,8314	0,8137	1,0217
	2019~2020	0,5039	0,884	0,57
	2020~2021	1,48	1,2235	1,2096
Sintra	2018~2019	0,9067	1	0,9067
	2019~2020	0,6793	1	0,6793
	2020~2021	1,3388	1	1,3388
Odemira	2018~2019	1,0077	1,06	0,9507
	2019~2020	0,7233	1,1795	0,6132
	2020~2021	1,0563	0,8679	1,2172
Santiago do Cacém	2018~2019	0,3179	0,3646	0,872
	2019~2020	0,9365	1,4472	0,6471
	2020~2021	1,3135	1,0793	1,217
Albufeira	2018~2019	0,8518	0,8796	0,9684
	2019~2020	0,413	0,7498	0,5508
	2020~2021	2,2426	1,82	1,2322
Aljezur	2018~2019	0,8178	0,859	0,9521
	2019~2020	0,6144	1,0238	0,6001
	2020~2021	1,0937	0,8861	1,2343
Castro Marim	2018~2019	1,1202	1,1963	0,9364
	2019~2020	0,6693	1	0,6693
	2020~2021	1,0665	0,8416	1,2672
Faro	2018~2019	0,9768	1	0,9768
	2019~2020	0,4972	0,8943	0,5559
	2020~2021	1,1027	0,899	1,2266
Lagoa	2018~2019	1,1962	1,2013	0,9958
	2019~2020	0,5734	0,9621	0,596
	2020~2021	1,3832	1,1702	1,1819
Lagos	2018~2019	0,7997	0,7757	1,031
	2019~2020	0,3644	0,6942	0,5249
	2020~2021	1,6785	1,3413	1,2514
Loulé	2018~2019	0,9583	0,8974	1,0678
	2019~2020	0,468	0,8085	0,5788
	2020~2021	1,6115	1,3263	1,2151
Olhão	2018~2019	0,966	1,0093	0,9571
	2019~2020	0,5473	0,9746	0,5616
	2020~2021	1,2239	0,9295	1,3168

Table D.30 - Malmquist Productivity Indexes (Continuation)

Dmu	Year	Total Factor Productivity Index (TFPCH)	Technical Change (TECH)	Technological Change (TECCH)
Portimão	2018~2019	0,6467	0,8501	0,7607
	2019~2020	0,3963	0,702	0,5645
	2020~2021	1,318	1,0424	1,2643
Silves	2018~2019	0,9403	0,9423	0,9979
	2019~2020	0,5291	1,0354	0,511
	2020~2021	1,5448	1,2178	1,2685
Tavira	2018~2019	1,0551	1,0678	0,9881
	2019~2020	0,466	0,7691	0,6059
	2020~2021	1,3451	1,1255	1,1951
Angra do Heroísmo	2018~2019	0,8918	0,8801	1,0134
	2019~2020	0,6102	0,8334	0,7322
	2020~2021	1,6695	1,6212	1,0298
Horta	2018~2019	1,2185	1,2142	1,0036
	2019~2020	0,442	0,5044	0,8763
	2020~2021	2,258	2,0059	1,1257
Lajes do Pico	2018~2019	1,075	1,1575	0,9287
	2019~2020	0,5704	0,638	0,894
	2020~2021	1,8501	1,6273	1,1369
Ponta Delgada	2018~2019	0,9501	0,985	0,9645
	2019~2020	0,5658	0,7563	0,7482
	2020~2021	1,0518	1,0024	1,0493
Santa Cruz das Flore	2018~2019	0,7102	0,7648	0,9287
	2019~2020	0,5362	0,6471	0,8286
	2020~2021	1,9925	1,6304	1,2222
Calheta (Madeira)	2018~2019	0,7423	0,7993	0,9287
	2019~2020	0,8301	1,0528	0,7885
	2020~2021	1,3754	1,1308	1,2163
Porto Santo	2018~2019	0,9934	1,0697	0,9287
	2019~2020	0,8427	1,1213	0,7515
	2020~2021	1,5163	1,2432	1,2197
Ribeira Brava	2018~2019	1,0555	1,1036	0,9565
	2019~2020	0,5061	0,7863	0,6437
	2020~2021	2,0431	1,7001	1,2018
Santa Cruz	2018~2019	1,8145	1,6742	1,0838
	2019~2020	0,2667	0,4542	0,5872
	2020~2021	1,1376	0,9155	1,2426
São Vicente	2018~2019	0,4723	0,4938	0,9566
	2019~2020	0,4803	0,628	0,7649
	2020~2021	1,6876	1,6388	1,0298
Mean		0,982957895	1,023637719	0,94732193

Table D.31 – Mean of the Malmquist Productivity Indexes

Dmu	Total Factor Productivity Index (TFPCH)	Technical Change (TECH)	Technological Change (TECCH)
Caminha	0,9015	0,8828	1,0307
Viana do Castelo	0,9243	1,0021	0,9309
Póvoa de Varzim	1,0571	1,1077	0,9324
Alcobaça	1,0710	1,2810	0,9070
Caldas da Rainha	0,9224	0,9238	0,9892
Lourinhã	0,8805	0,9606	0,9677
Óbidos	0,7098	0,7537	0,8976
Aveiro	0,9587	0,9408	0,9789
Leiria	1,1218	1,1841	0,9737
Marinha Grande	1,1389	1,3844	0,8991
Pombal	0,8390	0,8401	1,0345
Almada	0,8283	0,8394	0,9593
Oeiras	1,0894	1,1675	0,9538
Setubal	0,9384	0,9737	0,9338
Sintra	0,9749	1,0000	0,9749
Odemira	0,9291	1,0358	0,9270
Santiago do Cacém	0,8560	0,9637	0,9120
Albufeira	1,1691	1,1498	0,9171
Aljezur	0,8420	0,9230	0,9288
Castro Marim	0,9520	1,0126	0,9576
Faro	0,8589	0,9311	0,9198
Lagoa	1,0509	1,1112	0,9246
Lagos	0,9475	0,9371	0,9358
Loulé	1,0126	1,0107	0,9539
Olhão	0,9124	0,9711	0,9452
Portimão	0,7870	0,8648	0,8632
Silves	1,0047	1,0652	0,9258
Tavira	0,9554	0,9875	0,9297
Angra do Heroísmo	1,0572	1,1116	0,9251
Horta	1,3062	1,2415	1,0019
Lajes do Pico	1,1652	1,1409	0,9865
Ponta Delgada	0,8559	0,9146	0,9207
Santa Cruz das Flores	1,0796	1,0141	0,9932
Calheta (Madeira)	0,9826	0,9943	0,9778
Porto Santo	1,1175	1,1447	0,9666
Ribeira Brava	1,2016	1,1967	0,9340
Santa Cruz	1,0729	1,0146	0,9712
São Vicente	0,8801	0,9202	0,9171