future transportation

Article

Efficiency of Regional Airports: Insights on the Effect of Airline Type and Seasonal Variations in Traffic

Ioanna Pagoni * and Annitsa Koumoutsidi

Department of Shipping, Trade and Transport, University of the Aegean, 82132 Chios, Greece
* Correspondence: ipagoni@aegean.gr

Abstract: This paper aims at exploring the efficiency of regional airports, whose traffic is highly dependent on touristic flows, and the impact of some external factors such as low-cost airlines, charter air traffic and seasonality. The analysis focuses on the airport market in Greece within the time period from 2010 to 2016. A bootstrapped data envelopment analysis model is developed and the Malmquist Productivity Index is computed to estimate the total productivity change between 2010 and 2016. This is followed by a tobit regression model to estimate the impact of the external factors on the airport efficiency scores. Our findings indicate that the considered factors significantly affect airport efficiency. More specifically, the low-cost airlines and charter flights contribute to increasing airport efficiency, while the seasonality might be seen as an obstacle to improving airport efficiency. To the best of our knowledge, this research goes beyond any previous study in the Greek airport market and could be useful for several practitioners, such as airlines, airport operators and hotel businesses, as well as policy-makers and authorities.

Keywords: airport efficiency; regional airports; data envelopment analysis; low-cost carriers; charter airlines; seasonality

Citation: Pagoni, I.; Koumoutsidi, A. Efficiency of Regional Airports: Insights on the Effect of Airline Type and Seasonal Variations in Traffic. *Future Transp.* **2022**, *2*, 774–792. https://doi.org/10.3390/futuretransp2040043

Academic Editor: Jian Li

Received: 17 June 2022
Accepted: 15 September 2022
Published: 21 September 2022

1. Introduction

Regional airports constitute a vital part of the airport industry and are considered essential transport nodes, since they connect people, products, and services via point-to-point routes, and provide accessibility to the most remote areas of Europe. They also contribute to the development of the local communities, the enhancement of social cohesion, as well as enabling tourism development, leading to economic regeneration and growth [1,2].

Yet, small regional airports have several specificities and face a number of challenges. Many regional airports play a significant role in the handling of leisure traffic [3], thus the seasonality of the air traffic is regarded as the main challenge. In these airports, intense fluctuations can be observed both in daily and monthly volumes [4]. More specifically, a recent study by the Airports Council International (ACI), which investigated seasonality in more than 1000 airports worldwide, revealed that, in half of the studied airports, the most prevalent peak months are two months during the summer period [5]. This is especially the case for airports located in the Mediterranean region. Although seasonality might increase airport profitability [6], in peak season, airports suffer from congestion and overcrowded airport terminals, detracting from the users' satisfaction with the traveling experience.

At the same time, since the deregulation of the European air transport market, low-cost carriers (LCCs) have seized the opportunity to enter the aviation industry. The LCCs' capacity (in terms of available seat kilometers) accounted for 21% of the global capacity in 2018, up from 11% in 2004 [7]. On an annual basis, the LCCs' development continues to outpace that of the overall industry, with their capacity growing by 13.4% (between 2017 and 2018), almost doubling the overall industry growth rate of 6.9%. Although the continuous expansion of such airlines has required their operation in both primary and secondary airport markets [8], history has shown that the LCCs have focused their operations on regional, secondary airports. In addition, the LCCs often choose to offer their operations at underutilized airports, where the catchment area is underserved or there is the potential for attracting leisure travel stimulated by the low fares [9]. At the same time, many regional airports are seeking LCC traffic, as there are several examples of increased passenger numbers due to the LCC flights [10,11], while regional authorities consider that the attraction of the LCCs can be beneficial for the development of the local economy [12]. Thus, along with charter airlines, LCCs traditionally serve the leisure and tourism traffic in regional airports located in remote areas [3,13,14].

Both effects, the uneven distribution of the traffic over the year and the high rates in the LCCs and charter airlines' (CCs) growth, lead to a substantial challenge concerning whether the operational processes and infrastructure of regional airports are efficient. The risk of either under- or overutilized assets is therefore substantially higher than at large airports. Against this background, it is worthwhile to investigate the efficiency of regional airports and explore how their efficiency scores may be affected by the airport market conditions, such as the air traffic seasonality and the presence of low-cost and charter airlines. This research focuses on the regional airport market of Greece, which experiences the challenges mentioned above. Moreover, the Greek airport market is an interesting case, as it has gone through a transitional period in recent years, with the privatization of some regional airports in 2017. The non-parametric method of data envelopment analysis (DEA) is applied to calculate the efficiency of 15 regional airports in Greece, followed by the computation of the Malmquist Index, while tobit models using data between 2010 and 2016 are developed to estimate the impact of the prevailing factors, such as the seasonality and the presence of low cost and charter airlines, on airport efficiency.

The remainder of the paper is structured as follows. Section 2 presents the current literature regarding airport efficiency, while Section 3 describes the contextual setting of our study. Section 4 presents the methodology used, followed by the results of our analysis in Section 5 and our conclusions in Section 6.

2. Literature Review

Airport benchmarking is an important self-improvement tool that is used to identify an airport's own strengths and weaknesses, compare itself with others, and gain insights on how to improve efficiency. There are several techniques to evaluate airport performance and efficiency. The first group comprises investigations applying parametric methods, such as stochastic frontier models, which measure airport efficiency through econometric techniques [15–20]. The second group of contributions includes the application of a data envelopment analysis, which is a non-parametric method that measures the relative efficiency by comparing it with the possible production frontiers of the decision-making units, using linear programming [21]. A major attractiveness of DEA is its ability to treat a large number of units and handle multiple inputs and outputs to derive the relative efficiencies [22]. In this paper, a DEA analysis is performed at the selected study airports to compute their efficiency; thus, our review of the literature is concentrated on the contributions related to DEA in the airport industry.

The topic of airport efficiency has received the interest of numerous researchers and practitioners in the last few years, who have applied DEA to estimate airport performance. Some of these studies go one step further, by applying a second-stage regression analysis in order to explore the effect of a number of explanatory variables on airport efficiency. The airport size, ownership status, hub operations, and location are found to be the most frequent determinants studied by the researchers in terms of their impact on airport efficiency. Since a detailed analysis of the literature is out of the scope of this paper, the following text summarizes the key findings that have emerged from the past studies. Comprehensive analyses of airport efficiency in the literature can be found in several recent publications [23–26]. Concerning the airport size, larger airports are usually found to be more efficient than smaller ones [27–37]. This can be explained by the fact that large airports have decreasing returns of scale, as they are close to capacity saturation and are operating close to their physical frontier. However, some studies have shown that large and small airports do not have significant diversification in terms of their efficiency levels [38,39]. In terms of ownership, the results are not so clear. In some studies, airport privatization is found to positively affect the airport efficiency, with private airports being more productive than fully government-owned airports [28,30,40]. However, the results from Ablanedo-Rosas and Gemoets [39] and Lin and Hong [41] showed that there is not a significant difference in performance when airports are grouped by the ownership status, while other studies have stated that, involving the private sector, particularly under a monopoly, may not ensure airport efficiency gains [42,43]. With regards to hub operations, the current research indicates that the hub–spoke systems seem to provide a more efficient airport performance [40–50], while the small hubs consistently outperform the larger hubs in terms of relative efficiency [29]. The airport location has been the focus of much research related to airport efficiency [35,51–56]. An island location is found as a factor positively affecting airport efficiency, as the airports located on islands showed a more stable performance [57–59]. Finally, competition among nearby airports constitutes another key factor that influences airport efficiency, based on Huynh et al. [60] and Ha et al. [61].

Table 1 presents a detailed overview of the inputs and outputs that have been used in previous DEA studies, where it is indicated that the airport airside and landside characteristics (e.g., the runway, apron, terminal area), as well as the labor-related data, are commonly selected as inputs, while the passenger and freight traffic and aircraft movements are mostly used as outputs in the developed DEA models.

Table 1. Review of the inputs and outputs used in DEA studies.

	Inputs													Outputs						
			Airside		Landside					Financial Data										
Author	Airport area	Operational characteristics	Runway	Apron	Terminal	Gates/Bridges	Baggage claim	Check-in desks	Car parking area	Labor	Capital	Operations	Other Costs	Passengers	Aircraft	Cargo	WLU	Environmental	Revenues	Other
Ablanedo-Rosas and Gemoets [39]												•		•	•	•				
Adler and Golany [50]	•	•																	•	•
Assaf [53]										•	•			•	•	•				
Barros [47]			•	•	•					•				•	•	•				
Barros and Dieke [28,51]										•	•	•		•	•	•			•	•
Bazargan and Vasigh [29]			•			•						•	•	•	•	•			•	•
Button et al. [62]		•	•		•				•					•	•					
Carlucci et al. [30]										•	•		•	•	•	•			•	
Chang et al. [55]		•	•		•									•	•	•				
Chen and Lai [19]												•							•	
Choo and Oum [63]										•			•	•	•				•	
Coto-Millán et al. [31]										•	•	•		•	•	•				
Coto-Millán et al. [32]										•	•	•		•	•	•				
Curi et al. [33]			•	•						•				•	•	•				
Fernández et al. [64]					•					•	•			•		•			•	
Fragoudaki and Giokas [59]			•	•	•									•	•	•				
Fragoudaki and Giokas [65]			•		•					•				•	•				•	
Fragoudaki et al. [34]			•	•	•									•	•	•				
Ha et al. [61]			•	•						•				•		•				

Table 1. *Cont.*

	Inputs													Outputs						
			Airside		Landside					Financial Data										
Author	Airport area	Operational characteristics	Runway	Apron	Terminal	Gates/Bridges	Baggage claim	Check-in desks	Car parking area	Labor	Capital	Operations	Other Costs	Passengers	Aircraft	Cargo	WLU	Environmental	Revenues	Other
Huynh et al. [60]			•	•	•									•	•	•				
Karanki et al. [49]	•		•		•	•				•			•				•		•	
Lin and Hong [41]			•	•			•			•				•	•					
Martin et al. [58]			•	•	•		•								•		•	•		
Merkert and Assaf [66]			•		•					•				•	•	•				•
Merkert and Mangia [35]	•		•	•	•					•		•	•	•	•	•				
Merkert and Mangia [36]	•		•	•	•					•		•	•	•	•	•				
Oum et al. [15]			•		•					•			•	•	•				•	
Pels et al. [38]	•		•	•	•		•	•	•					•	•					
Perelman and Serebrisky [40]	•		•			•				•				•	•		•			
Pyrialakou et al. [67]		•	•	•	•	•	•	•		•				•	•					
Ripoll-Zarraga and Raya [56]										•		•	•	•	•	•			•	
Sarkis [45]			•			•				•		•		•	•				•	•
Scotti et al. [17]			•	•	•		•	•		•				•	•	•				
Tsekeris [54]		•	•	•	•									•	•	•				
Tsui et al. [48]			•		•					•				•	•	•				
Ülkü [37]			•							•		•		•	•	•			•	
Yoshida and Fujimoto [16]			•		•					•			•	•	•	•				
Yu [57]		•	•	•	•									•	•			•		

The review of the current state of the art indicates that various studies have been conducted on the efficiency of (small) regional airports, bringing new insights into their management. The findings indicate that increased aircraft movements, passenger numbers and cargo traffic are the main drivers for increasing the technical efficiency of small airports. In turn, the airport traffic volumes of regional airports are influenced by several internal and external factors that should be taken into account by the managers who seek to improve the efficiency of their airports. These might include the airport capacity, turnaround fees, airport competition, region tourism attractiveness, the presence of incentive schemes and airport ground accessibility [14]. It is also evident that the operational performance of small, regional airports is significantly affected by their ownership regime [68,69] and hub airline airport status [50]. However, the studies that account for the implications of seasonality and the operation of low-cost and charter airlines on airport efficiency are rather limited. Thus, the present paper seeks to provide evidence for the following research questions (RQ).

RQ1. What is the impact of the operation of low-cost airlines on airport efficiency?

Studies on the effect of LCCs on airport efficiency are a growing area of research during recent years. These studies initially performed the DEA to obtain the efficiency scores for the studied airports, and then developed regression models to estimate the impact of the LCCs on efficiency. More specifically, Coto-Millán et al. [32], Carlucci et al. [30] and Button et al. [62] developed tobit models, while Coto-Milan et al. [31] and Merkert and Assaf [66] employed a truncated normal regression model. The independent variable of LCCs was included in their models in different ways, such as the share of LCC passengers [30–32,66] or the number of LCC operators at the considered airports [64]. All these studies concluded that the demand growth generated by the introduction of low-cost carriers at airports resulted in a positive impact on airport efficiency. This finding is consistent with other studies that applied other methods for calculating airport efficiency, which indicated that LCCs positively affect the total productivity of airports [70]. However, interesting research by Choo and Oum [63] regarding U.S. airports, where LCCs operate in both major and secondary airports, indicated that the LCCs do not appear to contribute to airport efficiency, especially when major airports are considered.

RQ2. What is the impact of the operation of charter flights on airport efficiency?

Charter operations have attracted the attention of numerous studies [71,72], as they constitute a key player in the air transport market [73]. However, studies focusing on the impact of charter operations on airport efficiency are still limited. Fernández et al. [64] applied the stochastic frontier analysis and included the airport share of charter passengers as an explanatory variable in their model. Their findings revealed that, although LCCs positively affect airport efficiency, airports with high shares of charter air traffic appear to perform less efficiently. Given the fact that charter flights account for a high proportion of traffic in Greek regional airports, it is important to investigate the relationship between charter operations and airport efficiency.

RQ3. How does seasonality influence airport efficiency?

Recent statistics indicate that the number of international tourist arrivals increased to 1.4 billion in 2018, with a growth of 5.4% compared to 2017, while more than 50% chose to reach their destination by air transportation [74]. In touristic airports, the above numbers significantly increase during the summer period, leading to the well-known phenomenon of air traffic variation within the year, which is called seasonality. The phenomenon of seasonality and its interaction with airport operations has attracted the attention of several researchers [6,33,37,54,68,75]. Seasonality has been documented to be a positive effect on the profitability of small and regional airports [6]. Assuming that airport profitability and efficiency follow the same trend line, this could mean that seasonal variations have positive effects on airport efficiency [37]. However, other studies have concluded that seasonality displays a negative impact on airport efficiency [33,54,68]. Based on the above, seasonality is a factor that should be investigated in terms of its impact on airport efficiency.

This study focuses on the Greek airport market, where efficiency analyses have been conducted by a few studies [34,54,59,65,67,76]. These studies assessed the efficiency of Greek airports and examined the impact of several determining factors, such as the airport location, mixed military airport use, airport accessibility, and connectivity, as well as the hotel infrastructure near the airport. This paper enhances this literature by applying a two-stage approach to analyze the efficiency of Greek airports (through a bootstrapped DEA model), and quantitively estimate the impact of low-cost airlines, charter air traffic, airport location and seasonality (via the estimation of tobit regression models).

3. Contextual Setting

Greece possesses an extended air network, with 39 commercial airports located on the mainland and the Greek islands, covering the entire country. All the airports serve domestic flights, while many of them receive charter and international flights as well, especially during the summer. Some of them cease to operate as coordinated airports during the winter, while others handle almost exclusively domestic flights and accommodate much lower traffic levels than those they have been planned for. There are also some airports, such as Karpathos, Araxos, Nea Anchialos and Aktion, which operate only during the summer, with very low passenger traffic from November to April.

In 2019, Greek airports served 526,155 thousand flights, with more than 64 million passengers [77]. Overall, Greek air traffic exhibits seasonal demand volatility, with a major increase in the air traffic during the peak season, which starts in June and extends until September. Our analysis of the latest statistics indicates that the air traffic in the peak season accounts for about 57.9% of the total annual traffic. Seasonality is even more intense in some island airports, with five airports located on the Greek islands of Zakynthos, Corfu, Kos, Rhodes and Heraklion being included in the top ten airports with the highest seasonality [5]. This is also confirmed by our analysis (provided in Section 5.2), which reveals that these airports have a high Gini coefficient in terms of the air traffic.

Another characteristic of the Greek air network is the evident presence of low-cost airlines. The market share of the low-cost airlines in Greece has dramatically increased in recent years, starting from 15.3% in 2010 and climbing to 27.8% in 2016. Concerning the other types of airlines, 40.6% of the air traffic is served by full network airlines, while 31.6% corresponds to charter air traffic, for this year.

Finally, a hot topic for the Greek airport industry is privatization. In Greece, this trend began with the construction of the Athens International Airport in 2001, where a public–private partnership (PPP) was selected, and the airport ownership was divided between the Greek state and the private sector in a 55:45 stake. Then, in 2019, the ownership agreement of the Athens International Airport was extended for 20 years, for the period from 2026 to 2046. The regional airports entered the game of privatization in 2017. Until then, the regional airports in Greece were owned by the Greek state and were centrally managed by the Hellenic Civil Aviation Authority [77]. In December 2015, the Hellenic Republic Asset Development Fund and a newly established company called Fraport Greece (with stakeholders including the German airport operator Fraport AG and the Greek business development organization, Copelouzos Group) signed an agreement for the concession of 14 regional airports. This process was finalized in April 2017, by which time Fraport Greece was responsible for the management, operation, development and maintenance of these 14 regional airports. The HCAA retains its role as the regulator of aeronautical services and provider of air-traffic control services, as well as the manager of the remaining Greek airports. Airport privatization is still an ongoing process in Greece. The latest developments account for the concession of the remaining 23 regional airports, which have been categorized in three groups based on their passenger traffic. The objective of the Greek state is to cooperate with private investors and to find a PPP scheme similar to that of the 14 airports managed by Fraport Greece.

Table 2 presents some characteristics of the studied Greek airports. This paper focuses on 15 regional airports, which serve more than 90% (176.6 million passengers in 2010–2016) of the passenger traffic served by the regional Greek airports. Most of them are located on the islands of the Ionian and Aegean seas, while three of them are located on the mainland (SKG, KVA, KLX) and two in Crete (HER, CHQ).

Table 2. Characteristics of the study airports in Greece (sorted by their annual passenger traffic).

No.	Airport	Airport Code	Ownership Status (after 2017)	Annual Passenger Traffic (in 2016)	Passenger Traffic in Peak Period (in 2016) [%]
1	Heraklion	HER	Public	6,742,746	69%
2	Thessaloniki	SKG	Private	5,687,325	44%
3	Rhodes	RHO	Private	4,942,386	71%
4	Chania	CHQ	Private	2,953,278	61%
5	Corfu (Kerkira)	CFU	Private	2,764,559	76%
6	Kos	KGS	Private	1,901,495	75%
7	Santorini	JTR	Private	1,685,695	66%
8	Zakynthos	ZTH	Private	1,415,712	85%
9	Mikonos	JMK	Private	999,026	81%
10	Kefalonia	ELF	Private	538,199	83%
11	Mytilene	MJT	Private	411,285	46%
12	Kavala	KVA	Private	258,239	70%
13	Kalamata	KLX	Public	227,980	73%
14	Chios	JKH	Public	196,130	41%
15	Lemnos	LXS	Public	87,232	69%

Our study employs panel data from 2010 to 2016 for the aforementioned Greek airports. As shown in Figure 1, the vast majority of the studied airports are characterized by increasing levels of passenger traffic, with the airports of Kalamata (KLX), Mykonos (JMK) and Santorini (JTR) having the highest increase rates, in comparison with the 2010 levels. Nevertheless, the passenger traffic in some of them (Kos, Mytilene, Lemnos and Rhodes) has decreased in recent years.

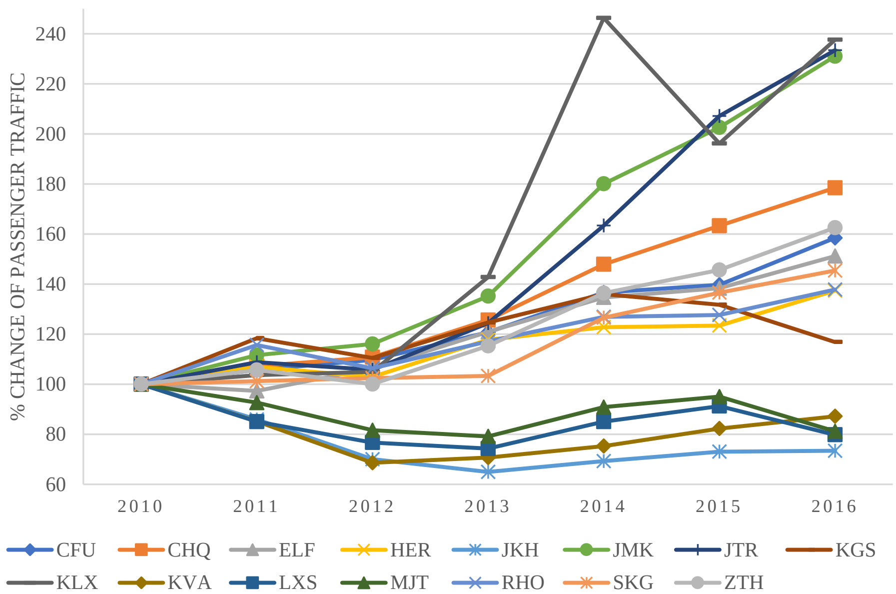

Figure 1. Evolution of passenger traffic in the study airports from 2010 to 2016.

4. Methodology and Data

Our approach includes a two-stage analysis, as follows. First, a bootstrapped data envelopment analysis is developed, using pooled data, to compute the efficiency of the studied airports from 2010 to 2016, and the Malmquist Productivity Index is computed to assess the productivity changes over this period. Then, tobit regression models are developed to estimate the impact of the LCCs, charter flights, seasonality and location of airports on islands on the airport efficiency. This section describes the methodological components of our analysis.

4.1. First Stage: Data Envelopment Analysis

Farrell [20] was the first to apply linear programming to measure productive efficiency. However, the first model was described by Charnes et al. [78], the founders of data envelopment analysis (DEA). DEA constitutes a non-parametric technique that estimates the efficiency levels of specific organizational units, which are called decision-making units (DMUs). From a computational perspective, DEA aims to identify the non-parametric, linear polygonal frontier that determines the efficiency of the studied DMUs, given the used inputs to produce a certain level of outputs. Depending on the scale assumptions that underpin the DEA model, constant returns to scale (CRS) and variable returns to scale (VRS) models can be developed. The first DEA model, CCR, assumes constant returns to scale to estimate the overall technical efficiency and reflect the fact that output will change by the same proportion as inputs are changed. However, this approach is valid when the DMUs operate under the condition of their optimal size. Imperfect competition, financial constraints, control steps, and other factors can cause the DMUs not to operate at their optimal size. To overcome these constraints, the BCC model [79], assuming variable returns to scale, was developed. This model accounts for the fact that the proportion between the inputs and outputs may not be constant along the frontier, and the production technology may exhibit increasing, constant and decreasing returns to scale, as it estimates the pure technical efficiency. DEA also provides two different approaches in the model's orientation, the input- and output-oriented model. The input-oriented model is used in order to minimize the used inputs and produce a certain level of outputs, while, when the aim is to maximize the produced outputs with a stable level of used inputs, the output-oriented model is more appropriate.

In this paper, the regional airports in Greece constitute our DMUs, with the inputs focusing on the airport infrastructure characteristics and the outputs referring to the traffic-related data. Hence, the output-oriented model is adopted because it is more rational to aim at the maximization of outputs (e.g., the traffic) instead of the minimization of the inputs (e.g., the airport's infrastructure cannot easily change once it is constructed). The VRS approach is required when there are size variations among the considered airports [59], while the CRS is used when the sample of DMUs are homogeneous. In this paper, the DEA efficiency scores are calculated under both the CRS and VRS models, obtaining the overall and pure technical efficiencies of the airports, respectively.

The output-oriented CRS and VRS models can be expressed by Equation (1), subject to the constraints given from Equations (2)–(4) [80].

$$max\theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

subject to:

$$\sum\nolimits_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0},\ i = 1,2,\ \ldots,\ m \tag{2}$$

$$\sum\nolimits_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta_0 y_{r0},\ r = 1,2,\ \ldots,\ s \tag{3}$$

$$\lambda_j \geq 0, j = 1,2,\ldots,n \tag{4}$$

Table 3 presents the variables and parameters of the above equations, along with their meaning.

Table 3. Variables associated with the output-oriented model.

Symbols	Meaning
θ_0	Efficiency score showing the proportional increase in output levels of the DMU 0 (airport 0)
ε	Small positive number ($0 < \varepsilon << 1$)
m	Number of inputs (i = 1,2, ... , m)
s	Number of outputs (r = 1,2, ... , s)
s_i^-	Input slack variables
s_r^+	Output slack variables
m	Number of inputs (i = 1,2, ... , m)
s	Number of outputs (r = 1,2, ... , s)
n	Number of DMUs (airports) (j = 1,2, ... , n)
λ_j	Intensity factor showing the contribution of airport j in the derivation of the efficiency of airport 0
x_{ij}	Amount of input i used by airport j
y_{rj}	Amount of output r produced by airport j

One of the main shortcomings of DEA is that it is not possible to apply a statistical inference, due to its deterministic nature. In fact, DEA estimates are affected by the sample data (inputs and outputs) and their variation, and they may be underestimated if the best "performers" in the population are not included in the sample (thus the efficient frontier obtained from the model cannot necessarily be indicative of the actual one). This fact could lead to biased DEA estimators. To mitigate this disadvantage, Simar and Wilson [81,82] have introduced a bootstrapping procedure as a tool of extracting the sensitivity of DEA scores towards the randomness that is attributed to the efficiency distribution. In this paper, the bootstrap DEA approach proposed by Simar and Wilson [83] is adopted to obtain bias-corrected efficiency scores for the studied Greek airports.

Finally, since panel data is used for our analysis, we decided to compute the Malmquist Productivity Index (MPI) to analyse the productivity change during the study period (from 2010 to 2016). This index was first established by Malmquist [84] and was further developed by Fare et al. [85]. Based on its values, the following interpretation can be made:

- If MPI = 1, the airport efficiency has remained the same;
- If MPI > 1, the airport has shown a positive productivity from year t to year $t + 1$;
- If MPI < 1, the airport productivity change from year t to year $t + 1$ is negative.

In terms of the data, we employ pooled data, consisting of a set of 105 observations covering the time period from 2010 to 2016 across the 15 Greek regional airports (as indicated in Table 2). To overcome the issues associated with the low discriminative power of the DEA model, the literature suggests that the number of DMUs should be greater by two- or three-times than the sum of the inputs and outputs. By pooling the DMUs belonging to multiple time periods, we treat the airports in each different time period as "different" DMUs. In this way, we achieve an increase in the number of DMUs, thus leading to a considerable enhancement of the discriminative power of the DEA model [86]. Moreover, according to the previous research [87,88], the time span of our study (seven years from 2010 to 2016) is rather short, avoiding unfair comparisons due to significant technological changes. In addition, the airport industry is characterized by limited technological changes within such time periods [88], which allows us to adopt such an approach, constructing a single metafrontier with the entire dataset.

The input and output variables used for the DEA assessment constitute infrastructure and operational characteristics, as shown in Table 4, along with their descriptive statistics. The inputs include the airport infrastructure characteristics, such as the runway length, terminal size, apron size and the number of check-in counters. As for the outputs, these concern the annual aircraft movements, the passengers served, and the cargo transported in each airport. These inputs and outputs were selected for our DEA analysis, based on the review of the existing literature and the data the authors had at their disposal. In addition, the number of selected inputs and outputs meets the constraints set by the literature regarding the number of DMUs used in the analysis, as presented in Cooper et al. [80]. All the above data were obtained after the manipulation of a database provided by the Hellenic Civil Aviation Authority for the study period. Concerning the DEA input and output variables, for readability reasons, the summary statistics for 2016 are presented. In addition, the evolution of the air traffic for each of the studied airports is depicted in Figure 1.

Table 4. Descriptive statistics of the variables used in the first- and second-stage analysis.

Variable	# Of Observations	Mean	Std. Dev.	Minimum	Maximum
First stage: DEA					
Inputs (year 2016):					
Runway length (m)	15	2533	490	1511	3348
Passengers terminal size (m^2)	15	14,815	15,036	1200	49,150
Apron size (m^2)	15	56,802	37,383	8000	140,000
Number of check-in counters	15	10.75	14.33	2	40
Outputs (year 2016):					
Aircraft movements	15	16,545	15,137	2684	48,622
Passengers (in thousands)	15	2054	2088	87	6743
Cargo (in tonnes)	15	711,338	8,198,538	0	1,530,787.7
Second stage: Tobit model explanatory variables *(years 2010–2016)*					
Market share of LCCs	105	0.186	0.116	0.000	0.465
Market share of CCs	105	0.321	0.159	0.054	0.671
GINI coefficient	105	0.470	0.166	0.118	0.676
Airport Location (=1 for island airports)	105	0.800	0.402	0.000	1.000

4.2. Second Stage: Tobit Regression Analysis

In order to explore the factors that influence airport efficiency, a regression model is estimated at the second stage, where the first-stage, bootstrapped DEA efficiency scores (dependent variable) are regressed against some explanatory variables. These variables aim to capture the associations with exogenous factors, that are basically not controllable by the studied airports but provide a better understanding of the contextual setting in which these airports operate.

Since the efficiency scores calculated in the first stage are bounded between zero and one, the tobit regression models are estimated. This method has been documented to be the most appropriate for two-stage DEA-based procedures, as it outperforms other parametric methods, providing consistent estimators through maximum likelihood techniques. Thus, it has been widely used in the airport literature for the second-stage analysis of DEA efficiencies [16,32,62]. The tobit model can be expressed as:

$$y_{it}^{*} = \alpha + \beta X_{it} + \varepsilon_{it} \tag{5}$$

$$\left.\begin{array}{r} y_{it} = y_{it}^{*},\ \ if\ 0 \leq y_{it}^{*} \leq 1 \\ y_{it} = 0,\ \ if\ y_{it}^{*} \leq 0 \\ y_{it} = 1,\ \ if\ y_{it}^{*} \geq 1 \end{array}\right\} \tag{6}$$

where y_{it}^{*} is an unobserved latent variable, y_{it} denotes the bootstrapped bias-corrected DEA efficiency scores for airport I in time t, X_{it} is the vector of the independent variables, α and β are the model coefficients to be estimated, and ε_{it} is an independently distributed error term, assumed to be normally distributed with zero mean and constant variance σ^2. In terms of the independent variables (X_{it}), these include (i) the market share of the low-cost airlines at each airport, (ii) the market share of the charter flights at each airport, (iii) the seasonality, expressed by the Gini coefficient in each airport, and (iv) geographical location, expressed as a dummy variable equal to one for the airports that are located on islands. We pool the data over seven years ($t = 1, \ldots, 7$) (from 2010 to 2016), which means that we have 105 observations for the 15 airports of our sample ($i = 1, \ldots, 15$). Since we are using panel data in our analysis, the tobit regression is additionally estimated by using cluster-robust standard errors to allow for correlation between the observations within the airport clusters. Table 4 presents the variables used for the first- and second-stage analysis.

5. Data Analysis and Results

5.1. DEA Scores

Table 5 presents the bootstrapped DEA efficiency scores, based on the pooled data of the selected airports for the study period (2010–2016). Both the CRS and VRS results are presented. Our analysis indicates that the airports of Heraklion (HER), Thessaloniki (SKG) and Kos (KGS) are included in the group of the best-performing airports with the CRS and VRS efficiency scores greater than 0.8, on average. This means that they were operating at the most productive scale, maximizing their aircraft movements, passenger and freight traffic and fully utilizing their inputs. In addition, the airports of Chios (JKH), Mytilene (MJT), Santorini (JTR), Chania (CHQ) and Rhodes (RHO) operated at above 50% (both considering the CRS and VRS scales). Finally, five airports operated with lower efficiency scores (at under 50%).

Table 5. Bootstrapped DEA efficiency scores for the study airports (2010–2016).

	2010		**2011**		**2012**		**2013**		**2014**		**2015**		**2016**		**Average**	
Airport	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**
SKG	1.000	1.000	0.920	0.920	0.905	0.905	0.838	0.838	0.936	0.936	0.966	0.966	1.000	1.000	0.938	0.938
KGS	0.912	0.931	0.928	0.946	0.789	0.831	0.884	0.921	0.944	0.999	0.909	0.962	0.807	0.853	0.882	0.920
HER	0.735	0.808	0.772	0.848	0.721	0.781	0.806	0.842	0.839	0.861	0.844	0.865	0.939	0.963	0.808	0.853
JKH	1.000	1.000	0.777	0.859	0.682	0.700	0.750	0.750	0.695	0.695	0.748	0.748	0.803	0.803	0.779	0.794
MJT	0.899	1.000	0.712	0.801	0.671	0.740	0.694	0.762	0.732	0.801	0.718	0.784	0.618	0.687	0.721	0.796
JTR	0.584	0.585	0.583	0.585	0.530	0.531	0.588	0.590	0.733	0.734	0.856	0.857	0.969	0.970	0.692	0.693
CHQ	0.617	0.629	0.615	0.621	0.578	0.619	0.628	0.693	0.722	0.815	0.794	0.900	0.868	0.983	0.689	0.751
RHO	0.584	0.607	0.630	0.661	0.573	0.603	0.631	0.664	0.684	0.719	0.688	0.724	0.742	0.781	0.647	0.680
CFU	0.364	0.365	0.380	0.382	0.394	0.395	0.433	0.434	0.490	0.492	0.501	0.503	0.568	0.570	0.447	0.449
KLX	0.347	0.524	0.323	0.487	0.328	0.496	0.386	0.583	0.563	0.855	0.493	0.745	0.591	1.000	0.433	0.670
JMK	0.304	0.334	0.298	0.326	0.302	0.331	0.342	0.375	0.467	0.513	0.505	0.554	0.591	0.649	0.401	0.440
ZTH	0.258	0.258	0.272	0.273	0.258	0.258	0.297	0.298	0.352	0.352	0.375	0.376	0.419	0.419	0.319	0.319
ELF	0.280	0.302	0.256	0.276	0.272	0.293	0.282	0.304	0.296	0.323	0.307	0.332	0.333	0.362	0.289	0.313
KVA	0.317	0.329	0.299	0.312	0.197	0.204	0.200	0.208	0.196	0.202	0.194	0.198	0.176	0.176	0.225	0.233
LXS	0.234	0.271	0.179	0.204	0.161	0.183	0.158	0.180	0.173	0.196	0.174	0.198	0.153	0.173	0.176	0.201

The above scores reveal the differences occurring in terms of efficiency during the study years. We observe that some airports had high efficiency scores throughout the whole period, while others had lower efficiency scores at the beginning of the study period but showed a positive pace of progress. Figure 2 depicts the productivity changes of the study airports from 2010 to 2016, computed as the MPI. Most of the airports are characterized by positive productivity changes (MPI > 1), while only four airports (Mytilene, Chios, Lemnos and Kavala) have an MPI of less than 1, indicating a negative productivity change from 2010 to 2016.

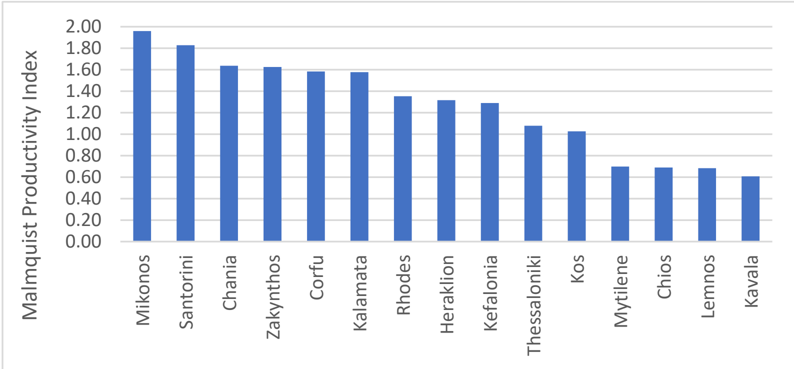

Figure 2. Airports' productivity changes over the study period.

5.2. Seasonality

In this paper, the seasonal concentration of passenger traffic at the study airports is investigated by computing the Gini coefficient for each airport for the years 2010–2016. This index can measure the degree of inequality in the number of passengers at an airport over a specific time period (a year, in our case) and ranges from 0 to 1. When the coefficient is close to 0, this means that the traffic is evenly distributed across the year, while a Gini coefficient close to 1 reveals a high seasonality. Figure 3 depicts the computed coefficients for each airport from 2010 to 2016. Although different levels of seasonality are observed among the study airports, the majority of them have Gini coefficients larger than 0.5, which means that they have considerable seasonality. More specifically, Zakynthos is the airport with the highest seasonality across the study years, followed by the airports located on the Aegean and Ionian islands (such as Mykonos, Kefalonia, Kos, and Corfu), while the three airports located on the North Aegean islands (Lemnos, Mytilene, Chios), as well as the airport of Thessaloniki, are not characterized by a considerable seasonal concentration.

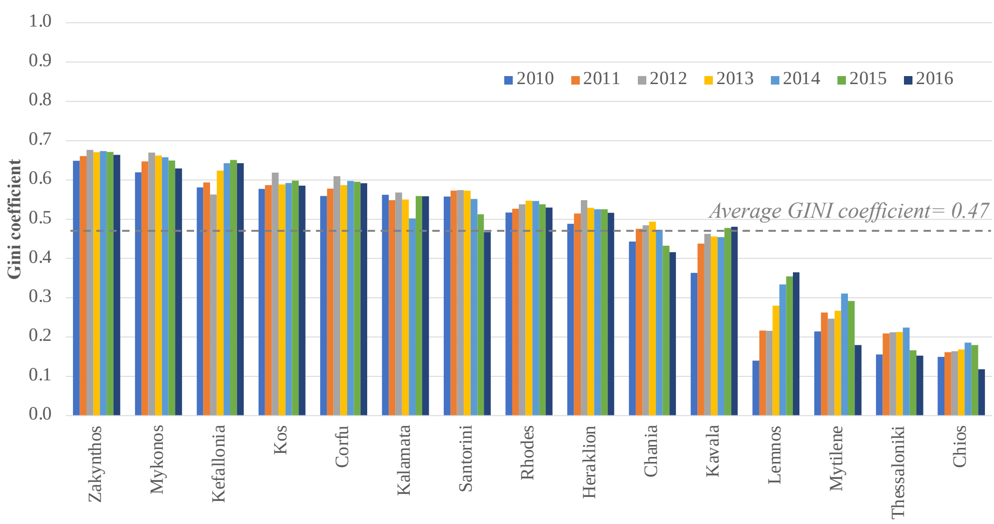

Figure 3. Gini coefficient for each airport across the study period (2010–2016).

5.3. Airline Type

In the studied airports, the presence of both the LCCs and CCs is very dominant in the period of 2010–2016. As Figure 4 depicts, for several Greek airports, a high proportion of the yearly traffic significantly relies on the presence of the LCCs and CCs. For instance, 6 out of the 15 airports (KLX, RHO, KGS, CFU, ELF, ZTH) have served more than 40% of the total passenger traffic handled by the charter airlines, while ZTH presented a share of up to 63.7%, being the busiest airport in terms of the charter air traffic (in market share terms). In addition, the low-cost airlines serve a significant percentage of the air traffic in most of the 15 studied airports, with JMK receiving the highest market share (about 37.5%).

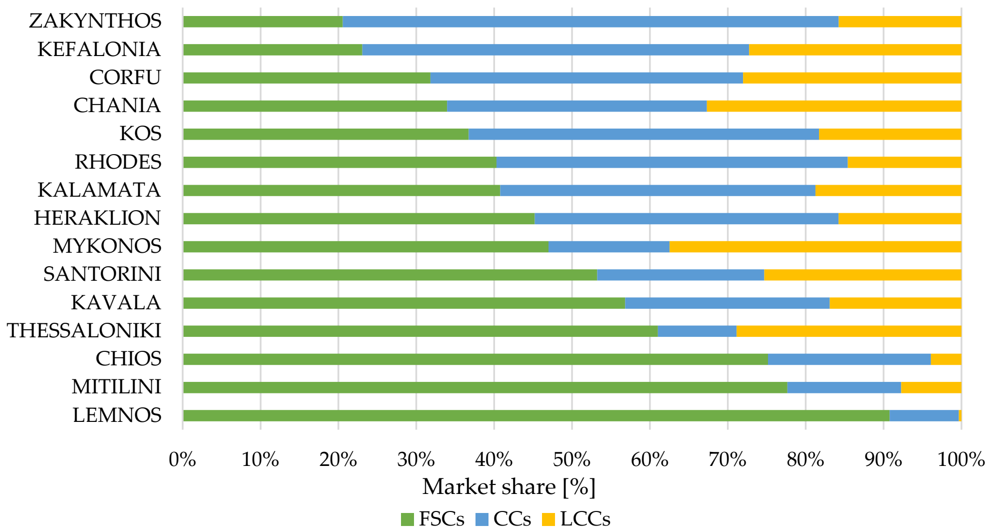

Figure 4. Market share among different airline types in the study airports (2010–2016).

Figure 5 provides a more detailed view of the historical passenger traffic of the low-cost airlines and charter flights in the study airports. The figure focuses on 10 of the 15 airports, since the remaining 5 airports had low passenger traffic with the low-cost and charter flights. Overall passenger traffic for both low-cost and charter flights showed an upward trend during the study period. However, charter flights are characterized by a more stable presence in the Greek airport market. It should be noted that our study period includes the year 2012, when the financial crisis in Greece led to downward movements in air traffic (as also presented in Figure 1). Even in 2012, the passenger traffic with the low-cost airlines in most regional airports in Greece increased, while the charter air traffic remained the same, or decreased, in many cases (e.g., Chania, Santorini, Mykonos, Heraklion, etc.).

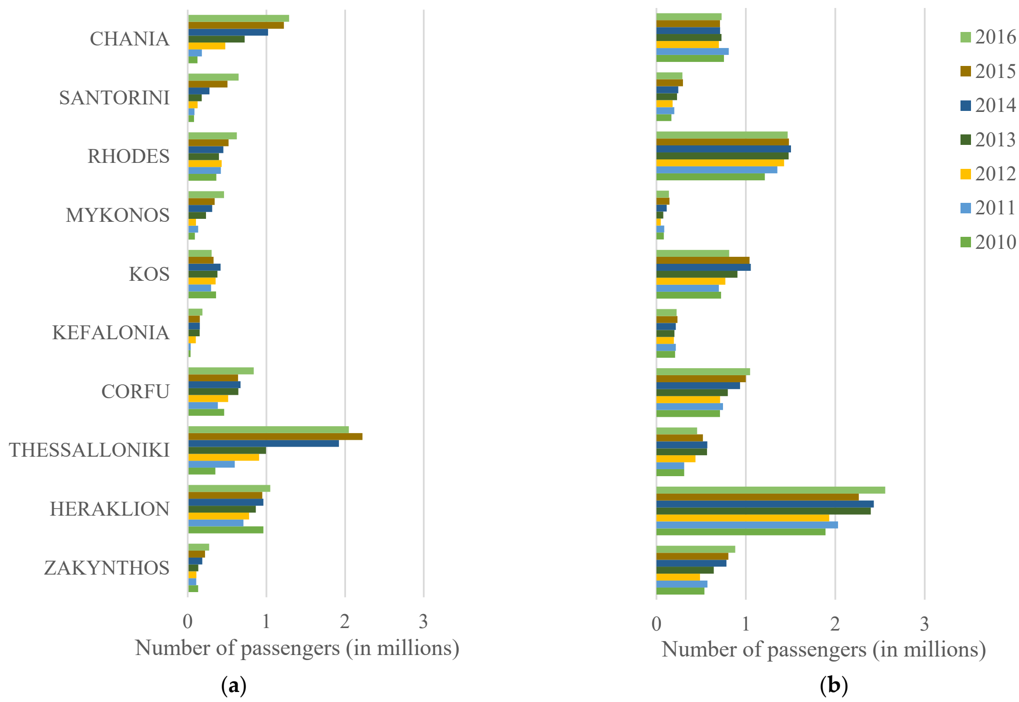

Figure 5. Evolution of passenger traffic for (**a**) low-cost airlines and (**b**) charter flights.

5.4. Second-Stage Results

The estimated results of the tobit regression models are presented in Table 6. More specifically, four models are estimated: (i) Models 1 and 2 consider the CRS DEA efficiency scores as dependent variables, while Models 3 and 4 regress the VRS DEA efficiency scores. In addition, Models 2 and 4 consider cluster-robust standard errors. It should be noted that all the models provide similar results, with slight differences in the magnitude of the estimated coefficients. Most of the considered coefficients are statistically significant (at 5% level) and the results (in terms of the signs of the coefficients) are in line with our expectations. More specifically, it is concluded that, the higher the share of low-cost airlines in the airport (in terms of the passenger traffic), the higher the efficiency. This finding is consistent with the previous research [31,62,70]. In addition, the variable of "charter air traffic" is significant, with a positive coefficient, indicating that the airports that have a high market share of charter flights are expected to have higher efficiency. This result is contrary to Fernández et al. [64], who reported that charter flights negatively affect airport efficiency. However, our results (both for the low-cost and charter flights) can be explained by the strong growth that these airlines have brought to the study airports, as presented in the previous section. In addition, the magnitude of the estimated coefficients (1.062 under the CRS and 1.022 under the VRS for the low-cost airlines versus 0.439 under the CRS and 0.437 under the VRS for the charter flights) indicate that the low-cost airlines play a more intense role in airport efficiency in comparison with the charter flights. We also found that the seasonality is statistically significant and has a negative coefficient, which means that, the higher the seasonal variations in an airport, the lower its efficiency. This finding can be attributed to the fact that airports with high seasonal variations may not operate efficiently due to the capacity constraints they may face in the peak seasons. Finally, the variable for the airport location on islands appears to positively affect the airport efficiency but was statistically significant only in Model 1.

Table 6. Estimation results of the tobit regression models.

Explanatory Variables	Model 1: CRS		Model 2: CRS & Cluster-Robust Standard Errors		Model 3: VRS		Model 4: VRS & Cluster-Robust Standard Errors	
	Coef (Std Error)	t-Value	Coef (Std Error)	t-Value	Coef (Std Error)	t-Value	Coef (Std Error)	t-Value
Constant	0.694 *** (0.075)	9.246	0.694 *** (0.188)	3.687	0.768 *** (0.082)	9.351	0.768 *** (0.197)	3.900
Low cost airlines	1.062 *** (0.233)	4.559	1.062 * (0.464)	2.289	1.022 *** (0.255)	4.015	1.022 * (0.472)	2.166
Charter air traffic	0.439 * (0.206)	2.135	0.439 (0.418)	1.049	0.437 * (0.224)	1.905	0.437 * (0.431)	1.015
Seasonality	−1.215 *** (0.223)	−5.449	−1.215 *** (0.285)	−4.263	−1.157 *** (0.243)	−4.747	−1.157 *** (0.279)	−4.149
Island location	0.130 * (0.057)	2.284	0.130 (0.116)	1.116	0.067 (0.062)	1.077	0.067 (0.159)	0.42
logSigma	−1.506 *** (0.070)	−21.401	−1.506 *** (0.131)	−11.487	−1.421 *** (0.071)	−19.899	−1.421 *** (0.111)	−12.789
Number of observations	105		105		105		105	

Notes: *** statistically significant at 1% level, * statistically significant at 5% level.

6. Conclusions

This paper investigates the efficiency of regional airports in Greece and the impact of some tourism-related elements, such as low-cost airlines, charter air traffic and seasonality. A two-stage analysis is employed, including the application of a pooled DEA model and the computation of the Malmquist Productivity Index, followed by Tobit regression models, by using airport-specific data for seven years (2010–2016). The model estimation results reveal that many regional airports in Greece operate at relatively high efficiency levels. As expected, the airports' efficiency has increased, due to the remarkable increase in passenger traffic in the last few years. Furthermore, the LCCs and CCs were found to be positive drivers of airport efficiency, which can be explained by the strong growth that they have brought to the regional airports in Greece within the study period. On the contrary, it was found that the seasonality (expressed as the Gini coefficient) hurts airport efficiency. Finally, it became evident that the geographical location of the regional airports affects their efficiency, indicating that the island airports operate more efficiently than those located on the mainland.

This paper contributes in various ways to the theory and practice. First, the paper enhances the literature about airport efficiency by providing additional insights regarding the airport efficiency of regional airports, and the impact of market- and tourism-related indicators, by using a two-stage approach. To the best of our knowledge, such insights have not been previously researched for the regional airports in Greece. In addition, our findings can be useful to practitioners within the air transport industry, including airport managers and airlines, as well as policymakers and regulators. This study can enhance the current evaluation process of the operational performance of airports, while it provides a better understanding of how the incoming low-cost and charter air traffic and seasonality could influence the airport efficiency, especially considering the transitional period that Greece has been going through over the last years, with the privatization of its regional airports. Our analysis demonstrates that, for each airport, the practitioners (e.g., airport managers, operators) need to find the "golden mean" among its inputs (e.g., the airport's characteristics), the external factors that influence efficiency, as well as its outputs (e.g., the traffic flows of passengers and freight). The airport operators should work closely with the airlines and local tourism stakeholders to identify potential new routes and increase the number of touristic flows, thus ensuring the sustainable development of the airports. In addition, considering the major contribution of the air transport sector on the economy and tourism in Greece, important policy implications can be drawn. The public authorities and airport operators should consider incentive schemes that would encourage further development of the airports' touristic markets and airline partnerships. However, as our results demonstrate, the issue of seasonality should be taken into consideration. The need for expanding the tourist period should be stressed, as this could be a measure to boost airport efficiency.

This paper focuses on three explanatory factors of airport efficiency. Further research should also pay attention to other factors affecting airport efficiency. The current DEA calculations could also be improved if the financial information were available. However, such data were not provided to the authors, due to confidentiality reasons. Finally, considering the pandemic of COVID-19, future research should also focus on exploring the impact of this challenging situation on airport efficiency. Several studies have already been published regarding the impact of the COVID-19 pandemic on airports and air transport in general [89–91].

Author Contributions: Conceptualization, I.P. and A.K.; methodology, I.P. and A.K.; validation, I.P. and A.K.; formal analysis, I.P. and A.K.; investigation, I.P. and A.K.; data curation, I.P. and A.K.; writing—original draft preparation, I.P. and A.K.; writing—review and editing, I.P. and A.K.; visualization, I.P. and A.K.; supervision, I.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Due to privacy reasons, the data are not provided publicly.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Halpern, N.; Bråthen, S. Impact of airports on regional accessibility and social development. *J. Transp. Geogr.* **2011**, *19*, 1145–1154. [CrossRef]
2. Kazda, A.; Hromádka, M.; Mrekaj, B. Small regional airports operation: Unnecessary burdens or key to regional development. *Transp. Res. Procedia* **2017**, *28*, 59–68. [CrossRef]

3. Strickland, J. Current challenges and future prospects for EU secondary airports. *Policy Dep. B Struct. Cohes. Policies* **2015**. Available online: https://www.europarl.europa.eu/RegData/etudes/STUD/2015/540373/IPOL_STU(2015)540373_EN.pdf (accessed on 19 September 2022).
4. Karlaftis, M.G. Demand forecasting in regional airports: Dynamic Tobit models with GARCH errors. *Sitraer* **2008**, *7*, 100–111.
5. Lucas, P.; Lioutov, I. Seasonal Markets. In *Airport Council International World Report*; Airport Council International: Montreal, QC, Canada, 2018.
6. Zuidberg, J. Exploring the determinants for airport profitability: Traffic characteristics, low-cost carriers, seasonality and cost efficiency. *Transp. Res. Part A Policy Pract.* **2017**, *101*, 61–72. [CrossRef]
7. International Air Transport Association (IATA). More Connectivity and Improved Efficiency—2018 Airline Industry Statistics Released. 2019. Available online: https://www.iata.org/en/pressroom/pr/2019-07-31-01/ (accessed on 9 October 2020).
8. Dobruszkes, F.; Givoni, M.; Vowles, T. Hello major airports, goodbye regional airports? Recent changes in European and US low-cost airline airport choice. *J. Air Transp. Manag.* **2017**, *59*, 50–62. [CrossRef]
9. Graham, A. Understanding the low cost carrier and airport relationship: A critical analysis of the salient issues. *Tour. Manag.* **2013**, *36*, 66–76. [CrossRef]
10. Červinka, M. Small regional airport performance and low cost carrier operations. *Transp. Res. Procedia* **2017**, *28*, 51–58. [CrossRef]
11. Humphreys, I.; Ison, S.; Francis, G. A review of the airport-low cost airline relationship. *Rev. Netw. Econ.* **2006**, *5*, 413–420. [CrossRef]
12. Francis, G.; Humphreys, I.; Ison, S. Airports' perspectives on the growth of low-cost airlines and the remodeling of the airport–airline relationship. *Tour. Manag.* **2004**, *25*, 507–514. [CrossRef]
13. De Neufville, R. Management of multi-airport systems: A development strategy. *J. Air Transp. Manag.* **1995**, *2*, 99–110. [CrossRef]
14. Dziedzic, M.; Njoya, E.T.; Warnock-Smith, D.; Hubbard, N. Determinants of air traffic volumes and structure at small European airports. *Res. Transp. Econ.* **2020**, *79*, 100749. [CrossRef]
15. Oum, T.H.; Yan, J.; Yu, C. Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. *J. Urban Econ.* **2008**, *64*, 422–435. [CrossRef]
16. Yoshida, Y.; Fujimoto, H. Japanese-airport benchmarking with the DEA and endogenous-weight TFP methods: Testing the criticism of overinvestment in Japanese regional airports. *Transp. Res. Part E Logist. Transp. Rev.* **2004**, *40*, 533–546. [CrossRef]
17. Scotti, D.; Malighetti, P.; Martini, G.; Volta, N. The impact of airport competition on technical efficiency: A stochastic frontier analysis applied to Italian airport. *J. Air Transp. Manag.* **2012**, *22*, 9–15. [CrossRef]
18. Barros, C.P.; Wanke, P.; Nwaogbe, O.R.; Azad, M.A.K. Efficiency in nigerian airports. *Case Stud. Transp. Policy* **2017**, *5*, 573–579. [CrossRef]
19. Chen, Y.-H.; Lai, P.-L. Determining the relationship between ownership and technical efficiency by using a dynamic stochastic production frontier approach. *J. Air Transp. Manag.* **2018**, *75*, 61–67. [CrossRef]
20. Adler, N.; Volta, N. Ranking methods within data envelopment analysis. In *The Palgrave Handbook of Economic Performance Analysis*; Palgrave Macmillan: Cham, Switzerland, 2019; pp. 189–224.
21. Farrell, M.J. The measurement of productive efficiency. *J. R. Stat. Soc. Series A* **2019**, *120*, 253–281. [CrossRef]
22. Sowlati, T.; Paradi, J.C. Establishing the "practical frontier" in data envelopment analysis. *Omega* **2004**, *32*, 261–272. [CrossRef]
23. Paraschi, E.P.; Georgopoulos, A.; Papatheodorou, A. Abiotic determinants of airport performance: Insights from a global survey. *Transp. Policy* **2019**, *85*, 33–53. [CrossRef]
24. Iyer, K.C.; Jain, S. Performance measurement of airports using data envelopment analysis: A review of methods and findings. *J. Air Transp. Manag.* **2019**, *81*, 101707. [CrossRef]
25. Lai, P.-L.; Potter, A.; Beynon, M. The Development of Benchmarking Techniques in Airport Performance Evaluation Research. *Transp. J.* **2012**, *51*, 305–337. [CrossRef]
26. Liebert, V.; Niemeier, H.M. A survey of empirical research on the productivity and efficiency measurement of airports. *J. Transp. Econ. Policy* **2013**, *47*, 157–189.
27. Abbott, M. Reform and efficiency of New Zealand's airports. *Util. Policy* **2015**, *36*, 1–9. [CrossRef]
28. Barros, C.P.; Dieke, P.U. Performance evaluation of Italian airports: A data envelopment analysis. *J. Air Transp. Manag.* **2007**, *13*, 184–191. [CrossRef]
29. Bazargan, M.; Vasigh, B. Size versus efficiency: A case study of US commercial airports. *J. Air Transp. Manag.* **2003**, *9*, 187–193. [CrossRef]
30. Carlucci, F.; Cirà, A.; Coccorese, P. Measuring and explaining airport efficiency and sustainability: Evidence from Italy. *Sustainability* **2018**, *10*, 400. [CrossRef]
31. Coto-Millán, P.; Casares-Hontañón, P.; Inglada, V.; Agüeros, M.; Pesquera, M.; Badiola, A. Small is beautiful? The impact of economic crisis, low cost carriers, and size on efficiency in Spanish airports (2009–2011). *J. Air Transp. Manag.* **2014**, *40*, 34–41. [CrossRef]
32. Coto-Millán, P.; Inglada, V.; Fernández, X.L.; Inglada-Pérez, L.; Pesquera, M. The "effect procargo" on technical and scale efficiency at airports: The case of Spanish airports (2009–2011). *Util. Policy* **2016**, *39*, 29–35. [CrossRef]
33. Curi, C.; Gitto, S.; Mancuso, P. New evidence on the efficiency of Italian airports: A bootstrapped DEA analysis. *Socio-Econ. Plan. Sci.* **2011**, *45*, 84–93. [CrossRef]

34. Fragoudaki, A.; Giokas, D.; Glyptou, K. Efficiency and productivity changes in Greek airports during the crisis years 2010–2014. *J. Air Transp. Manag.* **2016**, *57*, 306–315. [CrossRef]
35. Merkert, R.; Mangia, L. Management of airports in extreme winter conditions—Some lessons from analysing the efficiency of Norwegian airports. *Res. Transp. Bus. Manag.* **2012**, *4*, 53–60. [CrossRef]
36. Merkert, R.; Mangia, L. Efficiency of Italian and Norwegian airports: A matter of management or of the level of competition in remote regions? *Transp. Res. Part A Policy Pract.* **2014**, *62*, 30–38. [CrossRef]
37. Ülkü, T. A comparative efficiency analysis of Spanish and Turkish airports. *J. Air Transp. Manag.* **2015**, *46*, 56–68. [CrossRef]
38. Pels, E.; Nijkamp, P.; Rietveld, P. Inefficiencies and scale economies of European airport operations. *Transp. Res. Part E Logist. Transp. Rev.* **2003**, *39*, 341–361. [CrossRef]
39. Ablanedo-Rosas, J.H.; Gemoets, L.A. Measuring the efficiency of Mexican airports. *J. Air Transp. Manag.* **2010**, *16*, 343–345. [CrossRef]
40. Perelman, S.; Serebrisky, T. Measuring the technical efficiency of airports in Latin America. *Util. Policy* **2012**, *22*, 1–7. [CrossRef]
41. Lin, L.; Hong, C. Operational performance evaluation of international major airports: An application of data envelopment analysis. *J. Air Transp. Manag.* **2006**, *12*, 342–351. [CrossRef]
42. Graham, A. The objectives and outcomes of airport privatisation. *Res. Transp. Bus. Manag.* **2011**, *1*, 3–14. [CrossRef]
43. Willner, J.; Parker, D. The performance of public and private enterprise under conditions of active and passive ownership and competition and monopoly. *J. Econ.* **2007**, *90*, 221–253. [CrossRef]
44. Gillen, D.; Lall, A. Developing measures of airport productivity and performance: An application of data envelopment analysis. *Transp. Res. Part E Logist. Transp. Rev.* **1997**, *33*, 261–273. [CrossRef]
45. Sarkis, J. An analysis of the operational efficiency of major airports in the United States. *J. Oper. Manag.* **2000**, *18*, 335–351. [CrossRef]
46. Gerber, P. Success factors for the privatisation of airports—An airline perspective. *J. Air Transp. Manag.* **2002**, *8*, 29–36. [CrossRef]
47. Barros, C.P. Airports in Argentina: Technical efficiency in the context of an economic crisis. *J. Air Transp. Manag.* **2008**, *14*, 315–319. [CrossRef]
48. Tsui, W.H.K.; Balli, H.O.; Gilbey, A.; Gow, H. Operational efficiency of Asia–Pacific airports. *J. Air Transp. Manag.* **2014**, *40*, 16–24. [CrossRef]
49. Karanki, F.; Lim, S.H. The effects of use agreements on airport efficiency. *J. Air Transp. Manag.* **2020**, *84*, 101767. [CrossRef]
50. Adler, N.; Golany, B. Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. *Eur. J. Oper. Res.* **2001**, *132*, 260–273. [CrossRef]
51. Barros, C.P.; Dieke, P.U.C. Measuring the economic efficiency of airports: A Simar–Wilson methodology analysis. *Transp. Res. Part E Logist. Transp. Rev.* **2008**, *44*, 1039–1051. [CrossRef]
52. Tapiador, F.J.; Mateos, A.; Martí-Henneberg, J. The geographical efficiency of Spain's regional airports: A quantitative analysis. *J. Air Transp. Manag.* **2008**, *14*, 205–212. [CrossRef]
53. Assaf, A. The cost efficiency of Australian airports post privatisation: A Bayesian methodology. *Tour. Manag.* **2010**, *31*, 267–273. [CrossRef]
54. Tsekeris, T. Greek airports: Efficiency measurement and analysis of determinants. *J. Air Transp. Manag.* **2011**, *17*, 140–142. [CrossRef]
55. Chang, Y.-C.; Yu, M.-M.; Chen, P.-C. Evaluating the performance of Chinese airports. *J. Air Transp. Manag.* **2013**, *31*, 19–21. [CrossRef]
56. Ripoll-Zarraga, A.E.; Raya, J.M. Tourism indicators and airports' technical efficiency. *Ann. Tour. Res.* **2020**, *80*, 102819. [CrossRef]
57. Yu, M.-M. Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. *J. Air Transp. Manag.* **2004**, *10*, 295–303. [CrossRef]
58. Martín, J.C.; Román, C.; Voltes-Dorta, A. Scale economies and marginal costs in Spanish airports. *Transp. Res. Part E Logist. Transp. Rev.* **2011**, *47*, 238–248. [CrossRef]
59. Fragoudaki, A.; Giokas, D. Airport performance in a tourism receiving country: Evidence from Greece. *J. Air Transp. Manag.* **2016**, *52*, 80–89. [CrossRef]
60. Huynh, T.M.; Kim, G.; Ha, H.-K. Comparative analysis of efficiency for major Southeast Asia airports: A two-stage approach. *J. Air Transp. Manag.* **2020**, *89*, 101898. [CrossRef]
61. Ha, H.-K.; Wan, Y.; Yoshida, Y.; Zhang, A. Airline market structure and airport efficiency: Evidence from major Northeast Asian airports. *J. Air Transp. Manag.* **2013**, *33*, 32–42. [CrossRef]
62. Button, K.; Kramberger, T.; Grobin, K.; Rosi, B. A note on the effects of the number of low-cost airlines on small tourist airports' efficiencies. *J. Air Transp. Manag.* **2018**, *72*, 92–97. [CrossRef]
63. Choo, Y.Y.; Oum, T.H. Impacts of low cost carrier services on efficiency of the major U.S. airports. *J. Air Transp. Manag.* **2013**, *33*, 60–67. [CrossRef]
64. Fernández, X.L.; Coto-Millán, P.; Díaz-Medina, B. The impact of tourism on airport efficiency: The Spanish case. *Util. Policy* **2018**, *55*, 52–58. [CrossRef]
65. Fragoudaki, A.; Giokas, D. Airport efficiency in the dawn of privatization: The case of Greece. *J. Air Transp. Manag.* **2020**, *86*, 101821. [CrossRef]

66. Merkert, R.; Assaf, A.G. Using DEA models to jointly estimate service quality perception and profitability—Evidence from international airports. *Transp. Res. Part A Policy Pract.* **2015**, *75*, 42–50. [CrossRef]
67. Pyrialakou, V.D.; Karlaftis, M.G.; Michaelides, P.G. Assessing operational efficiency of airports with high levels of low-cost carrier traffic. *J. Air Transp. Manag.* **2012**, *25*, 33–36. [CrossRef]
68. Gutiérrez, E.; Lozano, S. Efficiency assessment and output maximization possibilities of European small and medium sized airports. *Res. Transp. Econ.* **2016**, *56*, 3–14. [CrossRef]
69. Chutiphongdech, T.; Vongsaroj, R. Technical efficiency and productivity change analysis: A case study of the regional and local airports in Thailand. *Case Stud. Transp. Policy* **2022**, *10*, 870–890. [CrossRef]
70. Bottasso, A.; Conti, M.; Piga, C. Low-cost carriers and airports' performance: Empirical evidence from a panel of UK airports. *Ind. Corp. Chang.* **2012**, *22*, 745–769. [CrossRef]
71. Williams, G. Will Europe's charter carriers be replaced by "no-frills" scheduled airlines? *J. Air Transp. Manag.* **2001**, *7*, 277–286. [CrossRef]
72. Castillo-Manzano, J.I.; Castro-Nuño, M.; López-Valpuesta, L.; Pedregal, D.J. Measuring the LCC effect on charter airlines in the Spanish airport system. *J. Air Transp. Manag.* **2017**, *65*, 110–117. [CrossRef]
73. Wu, C.; Hayashi, Y. The effect of LCCs operations and scheduled services deregulation on air charter business in Japan. *J. Transp. Geogr.* **2014**, *41*, 37–44. [CrossRef]
74. World Tourism Organization. *International Tourism Highlights, 2019 Ed.*; World Tourism Organization: Madrid, Spain, 2019.
75. Tembleque-Vilalta, M.; Suau-Sanchez, P. A model to analyse the profitability of long-haul network development involving non-hub airports: The case of the Barcelona–Asian market. *Case Stud. Transp. Policy* **2016**, *4*, 188–197. [CrossRef]
76. Psaraki-Kalouptsidi, V.; Kalakou, S. Assessment of efficiency of Greek airports. *J. Airpt. Manag.* **2011**, *5*, 170–186.
77. Hellenic Civil Aviation Authority (HCAA). Air Traffic Statistics 2019. 2019. Available online: http://www.ypa.gr/profile/statistics/2019/ (accessed on 10 October 2020).
78. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
79. Banker, R.D.; Charnes, A.; Cooper, W.W.; Maindiratta, A. A comparison of DEA and translog estimates of production frontiers using simulated observations from a known technology. In *Applications of Modern Production Theory: Efficiency and Productivity*; Springer: Dordrecht, The Netherlands, 1988; pp. 33–55.
80. Cooper, W.W.; Seiford, L.M.; Zhu, J. Data envelopment analysis: History, Models. In *Handbook on Data Envelopment Analysis*; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2011; pp. 1–40.
81. Simar, L.; Wilson, P.W. Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Manag. Sci.* **1998**, *44*, 49–61. [CrossRef]
82. Simar, L.; Wilson, P.W. A general methodology for bootstrapping in non-parametric frontier models. *J. Appl. Stat.* **2000**, *27*, 779–802. [CrossRef]
83. Simar, L.; Wilson, P.W. Estimation and inference in two-stage, semi-parametric models of production processes. *J. Econom.* **2007**, *136*, 31–64. [CrossRef]
84. Malmquist, S. Index numbers and indifference surfaces. *Trab. Estad.* **1953**, *4*, 209–242. [CrossRef]
85. Fare, R.; Färe, R.; Fèare, R.; Grosskopf, S.; Lovell, C.K. *Production Frontiers*; Cambridge University Press: Cambridge, UK, 1994.
86. Timmer, M.P.; Los, B. Localized Innovation and Productivity Growth in Asia: An Intertemporal DEA Approach. *J. Prod. Anal.* **2005**, *23*, 47–64. [CrossRef]
87. Asmild, M.; Paradi, J.C.; Aggarwall, V.; Schaffnit, C. Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *J. Product. Anal.* **2004**, *21*, 67–89. [CrossRef]
88. Adler, N.; Liebert, V. Joint impact of competition, ownership form and economic regulation on airport performance and pricing. *Transp. Res. Part A Policy Pract.* **2014**, *64*, 92–109. [CrossRef]
89. Forsyth, P.; Guiomard, C.; Niemeier, H.-M. COVID-19, the collapse in passenger demand and airport charges. *J. Air Transp. Manag.* **2020**, *89*, 101932. [CrossRef] [PubMed]
90. Serrano, F.; Kazda, A. The future of airports post COVID-19. *J. Air Transp. Manag.* **2020**, *89*, 101900. [CrossRef]
91. Suau-Sanchez, P.; Voltes-Dorta, A.; Cugueró-Escofet, N. An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it? *J. Transp. Geogr.* **2020**, *86*, 102749. [CrossRef] [PubMed]