Article
Exploring the Performance of International Airports in the Pre- and Post-COVID-19 Era: Evidence from Incheon International Airport

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Abstract: Considering the socio-economic importance of Incheon International Airport, this study explored the changes in its aeronautical and non-aeronautical efficiency between 2001 and 2021. The study was conducted to measure and observe the changes in efficiency during the pre- and post-pandemic era of COVID-19. We employed a two-stage analytical approach to obtain the results using a set of desirable and undesirable variables. For the first stage, we employed a novel network data envelopment analysis-window analysis model to find the efficiency measures; for the second stage, we applied the Tobit regression analysis to observe the impact of some control variables on efficiency levels. The empirical results from the efficiency analysis stage revealed that, although the pandemic negatively affected the efficiency of this airport, the gain from appropriate strategies mitigated the excessive efficiency decline. Moreover, aeronautical activities showed better efficiency than non-aeronautical activities during the study period. In addition, further investigation of the second-stage analysis implied that an outbreak of pandemic diseases such as COVID-19 would dramatically impact international hubs such as Incheon International Airport; however, focusing on the import and export activities, in addition to increasing the connectivity with other airports, would improve the efficiency.

Keywords: Incheon International Airport; efficiency; network data envelopment analysis–window analysis; network data envelopment analysis; two-stage analysis

1. Introduction

Airports are one of the most important infrastructures of the air transportation system. They facilitate airlines to serve passengers and handle aeronautical activities. In addition, airports are considered one of the main aviation centers to generate added value through non-aeronautical activities, such as duty-free shops, restaurants, passenger lounges, transfer services, and advertisements.

Similar to other developed economies, South Korea (hereafter, Korea) has also committed itself to enhancing the proper level of quality and quantity of air transport services by focusing on domestic and globalized hubs. Thus, Korean airports play a crucial role in facilitating high-quality service in both aeronautical and non-aeronautical production processes for a wide range of local and international passengers, air cargo, custom service, and the like in Northeast Asia. From its establishment in 2001, Incheon International Airport (IIA) has become the dominant hub in global air transport in Korea. In addition to a wide range of services for passengers and cargo, IIA has also been recognized as a smart and major airport in the accomplishment of marketing policies in the Korean air transport system [1].

Considering the socioeconomic role of domestic and international airports, concentrating on the performance analysis of these organizations has become an interesting subject.
for many researchers in the domain of air transport—e.g., [2,3]. Focusing on the performance analysis of airports would assist us in identifying the strengths and weaknesses of these organizations and recognizing the best practice for further benchmarking and future policy implications. To measure the efficiency level, non-parametric models such as the data envelopment analysis (DEA), stochastic frontier analysis (SFA), and distance function models are commonly used in airport efficiency assessment [2,3]. Thus, by employing linear programming (LP), DEA yields a benchmark index with relative efficiency scores for the sampled decision-making units (DMUs). The produced results contrast the efficiency scores with the frontier line, enveloped by the "best practice" observations as the most efficient DMUs in the sampled group [4].

Numerous DEA models have been applied to measure the efficiency score considering the production process of firm-level or industry-level studies. In addition to the conventional forms of DEA—e.g., [5–8], network data envelopment analysis (NDEA) models have recently become very popular among scientists, which assess the efficiency of complex production models such as air transport production models—e.g., [9–15]. However, except for some studies, such as those presented in e.g., [10,14], it is rarely possible to find the application of undesirable variables such as delays and canceled flights in the evaluation of airport efficiency. Moreover, considering the global risk of the COVID-19 outbreak on transport industries, a limited number of research articles already exist—e.g., [16–18]. Recently, [18] conducted a study on U.S.-based airline employees' responses to corporate preparedness for the COVID-19 disruptions to both domestic and international airline operations. Thus, using the NDEA window analysis, this study employed a set of desirable and undesirable variables to measure and investigate the efficiency change in IIA from the commencement of service in 2001 until the middle of the COVID-19 era, which is the end of the year 2021.

Subsequently, aiming to propose some policy implications, we employed some internal and external airport-related variables for the second stage of analysis to assess their impact on IIA's efficiency using a Tobit regression. In general, the results indicated that the aeronautical production process had a high level of efficiency during the study period, while the non-aeronautical approach did not perform well and had a considerable gap. The second stage of analysis revealed that the COVID-19 outbreak slightly affects the IIA efficiency; however, the results showed that IIA attempted to mitigate the negative impact of this pandemic by employing the available potential for cargo activities. In addition, we explain the influence of other external/internal control variables and suggest policies to improve efficiency.

The remainder of this paper proceeds as follows. First, Section 2 reviews the history of the aviation system in Korea and IIA, and then, the methodological literature related to airport efficiency evaluation is examined. Section 3 describes the data, methodology, and two-stage assessment process using the window analysis of NDEA and Tobit regression analysis employed in this study. Section 4 presents the empirical results and discussion. Finally, Section 5 summarizes the findings, limitations, and future policy implications.

2. Literature Review
2.1. History of Incheon International Airport

Globalization has been pervasive in all developed economies in recent decades. Undeniably, air transport systems play a crucial role in transporting domestic and international tourists, business travelers, and cargo. Owing to the deregulation, commercialization, and privatization in the sub-sectors of aviation systems in many countries, air transport systems tend to expand their level of dominance to gain more from aviation markets. One of the strategies has been to provide globalized hubs and airport infrastructure through connections with a wide range of domestic and international airports. The steady economic development, in addition to the high population density in Northeast Asia, including Korea, Japan, and China, have increased the demand for air transport services more intensely than in other parts of the world in the past few decades, as explored in [19–22].
Before IIA, the Gimpo International Airport was established in 1958. Afterward, the first IIA terminal was launched in the Korean air transport system in 2001 to commence a new era in the history of Korean air transport. In addition, from 2004 to 2009, Korea focused on the establishment and development of new airlines, such as T’way Airlines, formerly known as Hansung Airlines, as the first Korean LCC airline, established in 2004 [23], Jeju Air (2005), Airbusan (2007), Jin Air (2008), and Eastar Jet (2009).

In Korea, 17 airports, including five international and 12 domestic, support the Korean aviation industry. The central government, through the Ministry of Land, Infrastructure, and Transport, as well as the Ministry of National Defense, owns these airports. From the very beginning, IIA was recognized as one of the highly competitive airports in Northeast and Southeast Asia [19]. IIA is not only the main and dominant airport in Korea, but for seven years, that is, from 2005 to 2012, it was recognized as the best airport in the world with the highest rate of customer satisfaction reported by the Airport Council International [24]. In 2008, concourse A, with an area of 16.5 hectares was connected to the passenger terminal, which increased IIA’s passenger handling capacity by 50%, from 32 million to almost 44 million.

In 2018, seventeen years after launching the first terminal, IIA opened its second terminal, aiming to expand the number of services to passenger and cargo aircraft. Thus, IIA, by associating with 52 countries, serves 88 airlines and connects 173 cities to the Incheon and Seoul metropolitan areas, which makes it one of the global top five airports (IIA publications, 2020). In the global context, IIA has always been considered as one of the most important hub airports located in the Asia Pacific region. Currently, IIA has the capacity to serve 77 million pax per year. This capacity assigns IIA third place, after Istanbul airport by 63 million and before Hong Kong airport and Dubai airports, by 78 million and 90 million pax, respectively. To attain the momentum of expanding the share of passengers and cargo, in addition to expanding the number of connections with other international airports and serving airlines, IIA planned to develop the airport through a fourth phase of construction. In this phase, IIA expanded the area of the second terminal, aprons, parking lots, and roads and added one runway (from 2017 to 2024). Beyond that, IIA also planned to develop an Air-City, which includes the accommodation facilities such as hotels and integrated resorts, cultural and recreational facilities, logistics complexes, maintenance, and overhaul facilities. This expansion strategy would enable IIA to increase its share of the world’s aviation market and compete successfully with other large-scale rival airports. Due to the fourth expansion phase, IIA would expand its capacity to serve 106 million pax in the year 2024. The flight capacity would increase from 500,000 to 600,000 and cargo capacity also would increase from 5 million tons to 6.3 million tons.

Due to the severe COVID-19 outbreak in 2020 and the outcome of the travel ban from Korean borders and most of the involved nations, IIA experienced a −62.8% and −67.5% drop in the number of passenger aircraft movements from 2019 to 2020 and then to 2021, respectively. However, considering cargo aircraft movements, the figures reveal a strong increase of >75% and 146% for similar periods. Although the IIA attempted to cover the decline in the number of passenger aircraft movements by focusing on cargo-related activities, there was still a >−80% decline in aeronautical revenue, which negatively affected the efficiency of the IIA for the following years. The dataset indicates that non-aeronautical activities were more affected during the COVID-19 pandemic. Thus, in the period from 2019 to 2021, the non-aeronautical revenue experienced a drop of >−82%, which imposed significant financial damage on the Korean aviation system.
2.2. Theoretical Background

This study employed a two-stage analysis to evaluate the efficiency and its influencing determinants during the IIA lifetime. For the first stage, we developed an NDEA model aligned with the window analysis approach to measure and investigate the efficiency change in the IIA. For the second stage, we employed a Tobit regression analysis to explore the determinants of efficiency changes for the IIA. Therefore, to explore the theoretical background of this study, we had to concentrate on the following three integrated aspects: the DEA–window analysis, the two-stage NDEA, and the Tobit regression analysis.

2.2.1. DEA–Window Analysis

The concept of the DEA–window analysis was demonstrated to diminish the effect of an inadequate number of DMUs in the dataset while measuring the efficiency. This approach enables researchers to overcome the weak discrimination power of the DEA because of the small sample size [25]. A previous study [26] introduced the DEA–window analysis to measure the efficiency trend based on a common technology set. In this method, we define a certain window of time as a DMU. Therefore, the relative efficiency of each DMU is compared with that of others using DEA models [27].

There are several pieces of evidence pertaining to the application of a DEA–window analysis in different fields such as healthcare systems [28,29], the hospitality sector [30], urban air quality evaluation [31], banking [32,33], LCC airlines [34], and others. However, considering an airport efficiency analysis, there is a general lack of literature, except for a few examples. As a pioneer of the application of the DEA–window method in airport efficiency assessment, [35] evaluated airports in Taiwan. Furthermore, [36] utilized the DEA–window to measure the operational efficiency of major Asia-Pacific airports. Afterward, some East Asian airports in Japan, Hong Kong, China, and Korea were evaluated by [27]. Using panel data, [37] investigated the efficiency change between 2001 and 2005 among 21 Asia-Pacific airports. The efficiency of New Zealand airports using the DEA–window analysis has been explored in studies such as [38,39]. Considering Korean airports, the most recent application of this approach is noticeable in [40].

2.2.2. Two-Stage NDEA Method

DEA is a non-parametric method using LP, and it is employed to evaluate the relative efficiency of homogeneous DMUs. The method was developed by [41] with the assumption of constant returns to scale (CRS), formerly extended to the variable return to scale (VRS) by [42]. In addition to the traditional forms of DEA, the NDEA is more attractive for researchers aiming to evaluate the efficiency of complex production models (with more than a singular stage of production), such as higher education [43], banking [44,45], insurance [46,47], healthcare systems [48,49], and so forth.

Recently, due to the socioeconomic role of airports, their production models have been an interesting topic for researchers to assess the efficiency of these organizations. Among different methods of efficiency evaluation, SFA and DEA have been widely used to assess the efficiency of airports. Thus, owing to the application of SFA, examples such as [50–52] are observable. However, DEA shows certain advantages over SFA in this area, as shown in [53]. For example, DEA is a non-parametric method using LP to benchmark the efficiency of comparable DMUs with a multiple-input/multiple-output production possibility set, which does not require presumptions regarding the form of the production function, as explored in [11,43]. Moreover, compared with the econometrics models, DEA enables researchers to employ the set of price-based and quantity-based data to measure the efficiency scores at the same time.

The application of traditional DEA forms to assess complex production models has some drawbacks as well. Namely, the traditional DEA employs a set of inputs to produce a set of outputs in a “black-box” [54]; however, the inter-relationship between the intermediate goods and internal processes is neglected. Therefore, from the introduction of a two-stage NDEA by [55], and later by [46], the application of NDEA has become more
interesting for researchers to assess complex production models. There are several examples of using two-stage NDEA models to assess the efficiency of airports. Yu (2010) [56] is considered a pioneer in the application of NDEA in the airport efficiency assessment. Considering the sub-activities, including aircraft movement and aircraft loading movement, author of [56] divided airport operations and employed an NDEA to measure the efficiency of 1-year cross-sectional data for 15 Taiwanese airports. Later, authors of [14] employed a two-stage NDEA for data of 39 Spanish airports during 2008. Further, in a study [10] the same dataset as in [14] was employed to introduce a novel two-stage NDEA, which assessed the efficiency using a set of desirable and undesirable variables. Measuring the aeronautical and commercial efficiency of 10 East Asian airports, author of [57] employed a two-stage NDEA to panel data from 2009 to 2013 first, and then applied a regression analysis to assess the determinants of efficiency. In a similar study, Liu (2017) [9] splits airport services into aeronautical and non-aeronautical subprocesses, while assessing the efficiency using a multi-period NDEA. Except for aeronautical and non-aeronautical activities, measuring the efficiency of Italian airports, author of [58] divided the slack-based NDEA into the cost, operations, and revenue stages. In a recent study [59], authors investigated the efficiency of eight Chinese and four Asian (except China) airports with a panel of actual and forecasted data from 2014 to 2021 using an NDEA.

To assess the airport’s efficiency, the application of conventional DEA models using undesirable variables is evidenced in studies such as [35,40,60,61]; however, with the exception of [10,14], few studies addressed undesirable variables, while assessing the efficiency of airports using NDEA models. Thus, in this study, we extend our idea and modify the two-stage NDEA models from [62,63] to maintain the efficiency results based on our production model for airport efficiency.

2.2.3. Tobit Regression Analysis

Exploring the determinants of efficiency through a second-stage analysis is very popular among researchers, and there are several methods used to maintain this approach, such as ordinary least squares (OLS), truncated regression, and Tobit regression analysis. However, while assessing the efficiency measures, since the efficiency score in most of the DEA models lies within zero and unity and is commonly censored to the left or right, truncated regression and Tobit models are more applicable. Using the maximum likelihood estimation (MLE) empowers the Tobit model [64] to estimate the accurate coefficients of a regression analysis than other methods, which increases the popularity of the Tobit model among researchers.

The Tobit model is widely used in the assessment of airports’ efficiency in the second-stage analysis. Thus, [65] employed a Tobit regression analysis to explore the effects of environmental, structural, and managerial variables on the performance measures of airports in the second-stage analysis. Subsequently, [66,67] employed a two-stage analysis of DEA and Tobit to evaluate Argentinian and Chinese airports, respectively. Similarly, [38,50,68] and, most recently, [39] examined the joint application of the DEA and Tobit model to determine the influence of control variables on airport efficiency. In addition to the above literature, we summarized some of the notable papers measuring airport efficiency in Table 1 to select the appropriate variables for our study. In Table 1, we summarized the general methodologies, input, output, and intermediate variables, which were employed in related literature. In addition, we also noted the related variables if the articles used the second-stage analysis. Although we have explained some of these studies in the previous subsections, in Table 1, we aimed to focus on variation among efficiency models employed in airport efficiency analysis and the related variables.
### Table 1. Related literature and variables used.

<table>
<thead>
<tr>
<th>Article</th>
<th>Methodology/Period of Study</th>
<th>Input Variables</th>
<th>Intermediate Good/Second-Stage Analysis Variables</th>
<th>Outputs Variables</th>
</tr>
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<tbody>
<tr>
<td>[61]</td>
<td>DEA 2012</td>
<td>1. Number of runways; 2. number of taxiways; 3. Terminal area; 4. Number of employees</td>
<td></td>
<td>1. Number of total aircraft movements; 2. Number of domestic passengers; 3. Number of international passengers; 4. Number of total passengers; 5. Number of commercial aircraft movements; 6. Cargo (ton)</td>
</tr>
<tr>
<td>[68]</td>
<td>DEA, bootstrap DEA, Tobit regression. 2011</td>
<td>1. Airport infrastructure measures such as runway length in meters; 2. Apron size in square meters; 3. Passenger terminal size in square meters</td>
<td>Second stage variables: 1. Geographical location; 2. Connectivity (CPT); 3. The level of accommodation infrastructure (HTL); 4. Locations (LOC) served by the airport network; 5. The mixture of operations (MC), that is, civil and military use</td>
<td>1. The total number of passengers set as the first output; 2. The number of aircraft movements; 3. Cargo</td>
</tr>
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Table 1. Cont.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>[70]</td>
<td>DEA, Technological Gap Ratios (TGRs) 2001–2013</td>
<td>1. Number of full-time-equivalent airport employees; 2. Number of gates through which aircraft can be loaded; 3. Number of runways; 4. Total area of passenger terminals; 5. Average length of runways at each airport</td>
<td>1. Number of passengers arriving or departing by air at an airport (both terminal and transit passengers); 2. Weight of cargo and mail; 3. Aircraft movements; 4. Total revenue (aeronautical and non-aeronautical).</td>
<td></td>
</tr>
<tr>
<td>[72]</td>
<td>DEA 2009 &amp; 2015</td>
<td>1. Inputs runways; 2. Gates terminal; 3. Area (m2) total</td>
<td>Second stage variables: 1. Log of the distance between that airport to the closest one; 2. Dummy, if the airport is corporatized; 3. Number of airlines using the airport as its hub</td>
<td>1. Passenger; 2. Cargo; 3. Flight</td>
</tr>
<tr>
<td>[73]</td>
<td>SBM-DEA, Tobit 2012–2018</td>
<td>1. Terminal area; 2. Runway length; 3. Apron</td>
<td>Second stage variables: 1. GDP per capita; 2. The proportion of the tertiary industry in the GDP; 3. The number of tourists travelling to the city where the airport is located</td>
<td>1. Passenger throughput; 2. Cargo and mail throughput; 3. Number of aircraft movements</td>
</tr>
<tr>
<td>[76]</td>
<td>DEA 2006–2016</td>
<td>1. Number of employees; 2. Capital; 3. Expenses not directly related to capital and personnel</td>
<td></td>
<td></td>
</tr>
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3. Methodology

3.1. NDEA–Window Analysis

The conventional DEA was developed by [41] to benchmark the efficiency level among DMUs in a given sample. Efficiency is defined by the ratio of all outputs per input. This ratio is maximized when a DMU is located on the common frontier, which is enveloped by all DMUs. While using DEA models, two interrelated problems must be considered. First, there is a lack of discrimination power, and second, there is unrealistic weight dispersion, as explored in [77]. Compared with the number of input(s)/output(s) variable(s), the lack of discrimination power would lead to biased results, while the number of DMUs in the sample is not sufficient—e.g., [25,78]. In this case, the conventional DEA produces many efficient DMUs and is located on the frontier line. In contrast, when the input and
output weights have extreme or zero values, it leads to unrealistic weight dispersion for the DEA—e.g., [79–81].

To avoid the lack of discrimination power in the dataset while using a limited number of DMUs, it is possible to consider each cross-section of the panel data as one DMU. This condition can be applied while evaluating one organization to observe the efficiency change for a certain period. Previously, [26] introduced the DEA–window analysis to evaluate multi-period observations simultaneously as a cross-section by treating each specific window of time as an independent DMU in the same organization. Thus, this study employed quarter-based panel data for 20 years of the IIA lifetime (each quarter including the cumulative data for three consecutive months). We considered each quarter as an independent DMU in our dataset. Thus, from 2001 to 2021, we have a total of 84 DMUs in our efficiency measurement, which produces global results in our study.

3.2. NDEA–Window Analysis for the Aeronautical Production Model

Let us consider $x_{ij}$ and $y_{rj}$ as the inputs and outputs, respectively, where $i = 1, 2, \ldots, m$ and $r = 1, 2, \ldots, s$ for DMU$_j$, $j = 1, 2, \ldots, n$. Previously, [41] introduced the CCR model to measure the relative efficiency among $n$ DMUs assuming a constant return to scale (CRS) condition. Model 1 introduces the conventional linear form of the input-oriented CRS model:

$$
E_{0}^{CCR} = \text{Max} \sum_{r=1}^{s} u_{r} Y_{rj},
$$

subject to:

$$
\sum_{r=1}^{s} u_{r} y_{rj} - \sum_{i=1}^{m} v_{i} x_{ij} \leq 0; j = 1, 2, \ldots, n,$$

$$
\sum_{r=1}^{m} v_{r} x_{ij} = 1,$$

$$
u_{r}, v_{i} \geq 0, r = 1, \ldots, s, i = 1, \ldots, m,$$

(1)

where $u_{r}$ and $v_{i}$ are the non-negative weights of the output and input factors, respectively. We assume that DMU$_j$ is efficient, while the $E_{0}^{CCR}$ is equal to unity. Although the above model has been used in numerous studies to attain efficiency scores, it is a black box and does not reflect any intermediate process for complex activities with different levels of inputs, intermediate goods, and final outputs. Therefore, as stated before, since our production model includes two stages of processing for the DEA, we chose the NDEA rather than the conventional DEA form. To illustrate the model employed in this study, Figure 1 represents the schematic model for the two-stage network process, which transforms the inputs and intermediate goods to the final desirable and undesirable outputs for the aeronautical process.

![Figure 1. Schematic model for the aeronautical production process.](image-url)
Let us consider a general two-stage model for \( j \) number of DMUs using desirable (with the upper notation of \( D \)) and undesirable (with the upper notation of \( UD \)) inputs \( X^D_j = \{ x^D_{ij} : i = 1, 2, \ldots, k \} \) and \( Z^D_j = \{ z^D_{ij} : f = 1, 2, \ldots, l \} \), intermediate goods \( Y^D_j = \{ y^D_{ij} : r = 1, 2, \ldots, s \} \), and outputs \( W^D_j = \{ w^D_{ij} : t = 1, 2, \ldots, h \} \), respectively.

\[
\begin{align*}
\{ X^D_j, Z^D_j, W^D_j, Y^D_j \} & : \quad \begin{cases} 
\sum_{i=1}^{k} \lambda_i x^D_{ij} \leq X^D_j, \sum_{i=1}^{k} \lambda_i x^{UD,U}_{ij} \geq X^{UD,U} \\
\sum_{i=1}^{k} \lambda_i x^{UD,U}_{ij} \geq Z^D_j, \sum_{i=1}^{k} \lambda_i x^{UD,U}_{ij} \leq Z^{UD,U} \\
\sum_{i=1}^{k} \mu_i y^D_{ij} \leq Y^D_j, \sum_{i=1}^{k} \mu_i y^{UD,U}_{ij} \geq Y^{UD,U} \\
\sum_{i=1}^{k} \mu_i y^{UD,U}_{ij} \geq Y^D_j, \sum_{i=1}^{k} \mu_i y^{UD,U}_{ij} \leq Y^{UD,U} \\
Z^D_j = W^D_j, Z^{UD,U}_j = W^{UD,U} \\
\lambda_j, \mu_j \geq 0, j = 1, 2, \ldots, n
\end{cases}
\end{align*}
\]

To solve the DEA model using undesirable inputs/outputs, one approach is to transform the undesirable into a desirable variable in the opposite direction. This means that it is possible to treat the undesirable output (input) as a desirable input (output) exclusively for each stage of the model, as has been done previously \[63,82-84\]. Considering the production possibility set, the general fractional form of the input-oriented CRS model for \( DMU_0 \) would be written as Model 3:

\[
E_{0}^{General} = \max \left[ \sum_{p=1}^{l} p^D_{fj} x^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} x^{UD,U}_{ij} \right] \\
+ \left[ \sum_{f=1}^{r} u^D_{fj} y^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} y^{UD,U}_{ij} \right], \\
s.t. \left[ \begin{array}{l}
\sum_{i=1}^{k} \sum_{p=1}^{h} p^{D,D}_{fj} x^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} x^{UD,U}_{ij} \leq 0, \forall j, \\
\sum_{i=1}^{k} \sum_{p=1}^{h} p^{D,D}_{fj} x^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} x^{UD,U}_{ij} \leq 0, \forall j,
\end{array} \right]
\]

To change Model 3 to a linear form, we employed two steps of the Charnes–Cooper transformation method \[85\]. Therefore, Model 3 is converted into a general linear Model 4. Thus, as a result of two steps of the Charnes–Cooper transformation method, all of the prior weights changed to the non-negative weights \( v^D, v^D, p^D, p^D, p^D, u^D, u^D \), and \( u^D \).

\[
E_{0}^{General} = \max \left[ \sum_{f=1}^{r} p^D_{fj} x^D_{ij} + \sum_{i=1}^{k} p^{UD,U}_{fj} x^{UD,U}_{ij} \right] \\
\sum_{i=1}^{k} \sum_{p=1}^{h} p^{D,D}_{fj} x^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} x^{UD,U}_{ij} \leq 0, \forall j, \\
\sum_{i=1}^{k} \sum_{p=1}^{h} p^{D,D}_{fj} x^D_{0j} + \sum_{i=1}^{k} \sum_{p=1}^{h} p^{UD,D}_{fj} x^{UD,U}_{ij} \leq 0, \forall j,
\]

As shown in Figure 1, our study did not use the undesirable variable for the intermediate and input level data; therefore, the above general linear model can be summarized into the two-stage aeronautical NDEA Model 5 to measure the overall global efficiency scores:
Therefore, the general fractional model for the non-aeronautical production process is previously to measure the efficiency of aeronautical activities.

Using OLS models, it is possible to regress the performance measures (including efficiency and productivity scores) on some internal/external independent variables. Depending on the form of the input-oriented efficiency models, the efficiency measures are bounded between 0 and 1. Furthermore, these efficiency scores can be censored to the lower bound 0, upper bound 1, or both. Indeed, MLE enables the Tobit regression to estimate the unobservable scores from the censored side. Thus, assessing efficiency measures using the Tobit

\[
E^{\text{aero}}_0 = \max \left\{ \sum_{r=1}^{s} u^D_r y^D_0 + \sum_{f=1}^{l} p^D_f z^D_0 - \sum_{f=1}^{l} q^D_f w^D_f \right\},
\]
\[
s.t. \quad \sum_{f=1}^{l} p^D_f z^D_f - \sum_{r=1}^{s} q^D_r w^D_r \leq 0, \quad \forall j,
\]
\[
\sum_{r=1}^{s} u^D_r y^D_r - \sum_{f=1}^{l} q^D_f w^D_f - \sum_{r=1}^{s} u^\text{UD}_r y^\text{UD}_r \leq 0, \quad \forall j,
\]
\[
\sum_{f=1}^{l} q^D_f w^D_f + \sum_{r=1}^{s} u^\text{UD}_r y^\text{UD}_r = 1, \quad \forall j,
\]
\[
v^\text{UD}_r, v^D_f, p^D_f, u^\text{UD}_r, and u^D_f \geq 0,
\]
\[
r = 1, 2, \ldots, s; \quad f = 1, 2, \ldots, h; \quad i = 1, 2, \ldots, m; \quad c = 1, 2, \ldots, a; \quad j = 1, 2, \ldots, n.
\]

3.3. NDEA–Window Analysis for the Non-Aeronautical Production Model

Figure 2 shows a schematic model of the non-aeronautical production process. This flow was employed to develop the NDEA model for this part of the study. At the first stage of the NDEA model, we employed some independent and some shared inputs used previously to measure the efficiency of aeronautical activities.

![Figure 2. Schematic model for the non-aeronautical production process.](image)

To measure the overall efficiency of the non-aeronautical model, we employed a two-stage additive model, similar to the aeronautical model without undesirable values. In addition, for the second stage, we used an external input $x^'_{ij}, c = 1, 2, \ldots, a$, as well. Therefore, the general fractional model for the non-aeronautical production process is formulated as Model 6:

\[
E^{\text{non-aero}}_0 = \max \left\{ \sum_{r=1}^{s} u_r y_0 + \sum_{f=1}^{h} p_f z_0 \right\},
\]
\[
s.t. \quad \sum_{f=1}^{h} p_f z_0 - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad \forall j,
\]
\[
\sum_{r=1}^{s} u_r y_r + \sum_{f=1}^{h} p_f z_0 - \sum_{c=1}^{a} \delta_i x^'_{ij} \leq 0, \quad \forall j,
\]
\[
\sum_{i=1}^{m} v_i x_{ij} + \sum_{f=1}^{h} p_f z_0 + \sum_{c=1}^{a} \delta_i x^'_{ij} = 1, \quad \forall j,
\]
\[
\forall i, \delta_i, p_f, and u_r \geq 0,
\]
\[
r = 1, 2, \ldots, s; \quad f = 1, 2, \ldots, h; \quad i = 1, 2, \ldots, m; \quad c = 1, 2, \ldots, a; \quad j = 1, 2, \ldots, n.
\]

3.4. Second-Stage Analysis Using a Tobit Regression

This study was conducted based on a two-stage analysis using NDEA and Tobit regression models. Following the efficiency assessment, we employed Tobit models to provide further insights into the relationship between some influencing factors and efficiency levels. Using OLS models, it is possible to regress the performance measures (including efficiency and productivity scores) on some internal/external independent variables. Depending on the form of the input-oriented efficiency models, the efficiency measures are bounded between 0 and 1. Furthermore, these efficiency scores can be censored to the lower bound 0, upper bound 1, or both. Indeed, MLE enables the Tobit regression to estimate the unobservable scores from the censored side. Thus, assessing efficiency measures using the Tobit
The model is preferred over OLS estimation, as shown in [86,87]. The general Assumption 7 denotes the concept of the application of the Tobit model, while the dependent variable $e_j, j = 1, 2, \ldots, n$ (here, the efficiency score) is limited to $[0, 1]$. Referring to Assumption 7, we employ the general Tobit Model 8 to investigate the explanatory variables defined in Table 2:

$$e_j = \begin{cases} e_j^* & \text{if } 0 \leq e_j^* \leq 1 \\ 0 & \text{if } e_j^* < 0 \\ 1 & \text{if } e_j^* > 1 \end{cases}, \quad (7)$$

$$e_j^* = \beta_0 + \beta_k X_{kj} + \epsilon_j^*, \ \forall \ j, \ k = 1, 2, \ldots, K \text{ and } j = 1, 2, \ldots, n, \quad (8)$$

where $e_j$ is the efficiency score, $e_j^*$ is the unobservable independent variable estimated using the MLE, $\beta_0$ is the intercept, $\beta_k$ is the vector of the coefficient estimated parameters, and $\epsilon_j^*$ is a set of independent error terms, which are randomly distributed with zero mean and variance $\sigma^2$. To select the best fit for our second-stage analysis, we employ the forward step selection and log-likelihood ratio (L-R) test, as explained in the results section.

**Table 2. Summary statistics of data used in the DEA and Tobit models.**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
<th>Max</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aeronautical Process</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aeronautical revenue (Billion KRW)</td>
<td>Total amount of revenue from aeronautical production process</td>
<td>456.00</td>
<td>1.92</td>
<td>67.81</td>
<td>131.30</td>
</tr>
<tr>
<td>Passenger (Million)</td>
<td>Total number of passengers</td>
<td>18.08</td>
<td>0.15</td>
<td>4.62</td>
<td>8.83</td>
</tr>
<tr>
<td>Cargo (1000 ton)</td>
<td>Total volume of cargo</td>
<td>861.38</td>
<td>11.04</td>
<td>124.24</td>
<td>612.56</td>
</tr>
<tr>
<td>Delay (Undesirable output)</td>
<td>Total number of delayed flights</td>
<td>7234.00</td>
<td>39.00</td>
<td>1763.02</td>
<td>2098.43</td>
</tr>
<tr>
<td>Canceled flights (Undesirable output)</td>
<td>Total number of canceled flights</td>
<td>382.00</td>
<td>2.00</td>
<td>68.99</td>
<td>105.73</td>
</tr>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The number of runways</td>
<td>Total number of available runways</td>
<td>3.00</td>
<td>2.00</td>
<td>0.48</td>
<td>2.64</td>
</tr>
<tr>
<td>Terminal area (1000 m²)</td>
<td>Total available area of terminals</td>
<td>1062.00</td>
<td>508.00</td>
<td>195.68</td>
<td>689.07</td>
</tr>
<tr>
<td>Parking lot capacity</td>
<td>Total number of available terminals</td>
<td>32,798.00</td>
<td>22,654.00</td>
<td>3983.31</td>
<td>24,586.19</td>
</tr>
<tr>
<td>Fixed assets (Billion KRW)</td>
<td>Total amount of fixed assets</td>
<td>12,500.00</td>
<td>6010.00</td>
<td>2063.24</td>
<td>8460.95</td>
</tr>
<tr>
<td>Employees (Aeronautical)</td>
<td>Total number of full-time aeronautical staff</td>
<td>496.00</td>
<td>183.00</td>
<td>100.75</td>
<td>778.83</td>
</tr>
<tr>
<td>Employees (non-aeronautical)</td>
<td>Total number of full-time non-aeronautical staff</td>
<td>1162.00</td>
<td>522.00</td>
<td>205.61</td>
<td>778.83</td>
</tr>
<tr>
<td><strong>Intermediate Goods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Passenger aircraft movement (1000 movements)</td>
<td>Total number of aircraft movement</td>
<td>103.62</td>
<td>0.87</td>
<td>25.63</td>
<td>55.24</td>
</tr>
<tr>
<td>Cargo aircraft movement (1000 movements)</td>
<td>Total number of cargo aircraft movement</td>
<td>24.90</td>
<td>0.14</td>
<td>4.02</td>
<td>8.85</td>
</tr>
<tr>
<td><strong>Non-aeronautical process</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-aeronautical revenue (Billion KRW)</td>
<td>Total amount of revenue from aeronautical production process</td>
<td>675</td>
<td>1.90</td>
<td>136.22</td>
<td>207.92</td>
</tr>
<tr>
<td>Customer satisfaction</td>
<td>Overall satisfaction for commercial facilities (Scale 1–5)</td>
<td>5.00</td>
<td>4.59</td>
<td>0.12</td>
<td>4.78</td>
</tr>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terminal area (1000 m²)</td>
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<td>55.24</td>
</tr>
<tr>
<td>Passenger (Million)</td>
<td>Total number of passengers</td>
<td>18.08</td>
<td>0.14</td>
<td>4.62</td>
<td>8.83</td>
</tr>
</tbody>
</table>
Table 2. Cont.

<table>
<thead>
<tr>
<th>Independent Variables for Tobit Models</th>
<th>Yes = 8 quarters</th>
<th>No = 76 quarters</th>
<th>-</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pandemic era Dummy variable for coronavirus pandemic</td>
<td>51.71</td>
<td>10.14</td>
<td>10.37</td>
<td>29.77</td>
</tr>
<tr>
<td>Import (Million USD) Total amount of import handled by IIA</td>
<td>53.02</td>
<td>10.68</td>
<td>11.44</td>
<td>32.60</td>
</tr>
<tr>
<td>Export (Million USD) Total amount of export handled by IIA</td>
<td>189.00</td>
<td>137.00</td>
<td>16.24</td>
<td>175.43</td>
</tr>
<tr>
<td>Connectivity destination Total number of connections with other airports</td>
<td>90.00</td>
<td>60.00</td>
<td>10.11</td>
<td>81.95</td>
</tr>
<tr>
<td>Operating Airlines Total number of operating airlines</td>
<td>5.94</td>
<td>0.03</td>
<td>1.90</td>
<td>1.95</td>
</tr>
<tr>
<td>LCC Cargo (1000 Ton) Total volume of cargos served by LCC flights</td>
<td>15.91</td>
<td>0.12</td>
<td>4.52</td>
<td>6.14</td>
</tr>
<tr>
<td>Local passenger (Million) Total number of local passengers served by IIA</td>
<td>11.48</td>
<td>0.31</td>
<td>2.85</td>
<td>5.04</td>
</tr>
<tr>
<td>Int. Passengers (Million) Total number of international passengers served by IIA</td>
<td>6.43</td>
<td>0.16</td>
<td>1.47</td>
<td>2.86</td>
</tr>
</tbody>
</table>

3.5. Data

In this study, we attempted to evaluate the IIA efficiency using a set of variables related to aeronautical and non-aeronautical production processes. The dataset covered 84 quarters (3 months for each quarter) of data between 2001 and 2021. Following the related literature, we employed five inputs, two intermediate goods, three desirable outputs, and two undesirable outputs for the aeronautical production process. Likewise, we employed three inputs, one intermediate good, one external input for the second stage, and one output for the non-aeronautical model. Table 2 presents the descriptions and statistics of the dataset. In addition to aeronautical production, we also explained the employed variables in the non-aeronautical production process. Moreover, we added the data descriptions and statistics of some internal and external variables, which were applied in the second stage of analysis using Tobit models. The statistical data consist of classified information collected by the IIA and attained directly from the IIA to be employed in this study.

To illustrate the dataset further, we defined the input set for both aeronautical and non-aeronautical production processes. Specifically, we used the number of runways, the total area of the terminals, the total parking lot capacities, the number of aeronautical employees, and fixed assets as the input set for the aeronautical production process. Here, since our NDEA model did not necessarily concentrate on cost efficiency, we employed quantity-based information for some variables such as the number of runways, the total area of the terminals, the total parking lot capacities, and the number of aeronautical employees. Moreover, due to the inconsistency in the quarter-based dataset related to the current assets, instead of employing the total assets, we utilized the fixed assets as a proxy for the airport’s capital stock. Passenger aircraft movements and cargo aircraft movements were used as intermediate goods between the first and second NDEA stages for the aeronautical production process. Since there is a high level of correlation between airport revenue and aircraft movements, these variables were selected to reflect the input requirements for the second stage of our NDEA model, as was done in similar studies [9,10,14,15,59]. To illustrate the output set for the second stage of the NDEA model for aeronautical activities, we employed the total number of passengers, the total volume of cargoes, and aeronautical revenue as desirable outputs; the total number of delayed flights and the total number of canceled flights were considered as undesirable outputs. The evidence of utilization of the abovementioned input/output variables is observable in prior studies [10,50,61,68–70,72].

Regarding the non-aeronautical production process, we employed the total area of terminals, the total parking lot capacities, and the total number of non-aeronautical employees as inputs; the total passenger aircraft movements and the number of passengers were considered as intermediate goods for the first stage. For the second stage of the NDEA model, in addition to the intermediate goods, we used flight delays as an external input, which would positively impact the efficiency of this production process. Regardless of the nature of this variable, we assume that this undesired output, produced from aeronautical activities, can play a positive role in non-aeronautical activities. Finally, we employed the non-aeronautical revenue and average customer satisfaction for commercial facilities as the outputs of the second NDEA stage. All financial statements were adjusted using the
gross domestic product deflator for the period 2001–2021. The base year was 2015. To confirm the accuracy of the selection of the input/output variable for each NDEA stage, we examined the dataset using the Pearson correlation test. The results imply positive and significant coefficients for the pairwise comparison of the input/output variables of each stage. Moreover, we also examined the multi-collinearity among independent variables employed in Tobit models.

To observe the pattern of changes in data for the period of study, we investigated the rate of changes for each variable using the annual average, first between 2001–2019, and second from 2019–2021. The figures indicated, that there was a significant +390% growth rate for the passengers served by IIA and also +132% for the volume of cargo between 2001 to 2019. However, considering the changes between 2019 to 2021, a significant drop of −95% is considerable. The volume of cargo experienced +21% growth for the same period. The observations on aeronautical and non-aeronautical revenues demonstrated a +401% and +865% variation from 2001 to 2019. However, during the COVID-19 period, we observed a −81% and −82% drop for these variables.

Passenger aircraft movements and cargo aircraft movements also experienced +365% and +145% growth between 2001–2019, and −91% and +20.1% between 2019–2021, respectively. One runway and one terminal were added to the IIA between 2001 to 2019 and did not change from 2019 to 2021. Terminal area and parking lots experienced +109% and +45% growth from 2001 to 2019. From 2019 to 2021, no variation was measured. As one of the main input variables, the investigation in fixed assets indicated +87% growth for the period of 2001 to 2019. Nearby +8% growth was estimated for fixed assets between 2019–2021. The number of aeronautical and non-aeronautical employees had grown +145% and +120% from 2001 to 2019, respectively. A small growth of +5% and 0.3% were found between 2019 to 2021 for these variables. Due to the expansion of IIA activities, undesirable variables such as delays and canceled flights had experienced +764% and +20% growth from 2001 to 2019. However, these measures had faced a −89% and −82% decline from 2019 to 2021.

4. Results and Discussion

In this section, we first obtained the efficiency results using the window analysis of our NDEA model. Next, considering the aeronautical activities, we measured the coefficients of internal/external influencing parameters on the efficiency of IIA using different Tobit models. We examined the Tobit models and selected the best fit using the L-R test. Finally, we calculated the measures and summarized the results using visualization techniques.

4.1. Estimated Results of NDEA Models and Technical Efficiencies

Figure 3 shows a histogram of the global results of the efficiency scores for both processes. Figure 3a shows the average (blue line) and median (red line) efficiency scores located to the right (unity), which indicates that the trend toward one tail is very significant. Moreover, as displayed in the figure, most efficiency occurrences pertain to scores between 0.95 and 1.0. Approximately 0.80% of global efficiency scores exceed 0.85; nevertheless, regarding high-level efficiency observations, only 20% of the total observation score is <0.8. The findings indicated that, in general, the aeronautical production process showed strong efficiency during the study period.
Considering the non-aeronautical production process (Figure 3b), approximately 45% of the observations had low-level efficiency scores (<0.65). Only 55% of observations with high-efficiency scores reveal the necessity of improving efficiency in the commercial activities of this organization. The findings indicated that a very limited number of observations had a technical efficiency <0.35. The majority of observations are between 0.6 and 0.8.

Compared with the aeronautical production process, the non-aeronautical production process did not show a considerable efficiency result. The average and median of 0.68 and 0.69, respectively, indicate that there is still ample room for improvement, which must be considered by the IIA managerial board to achieve a better efficiency level.

As shown in Figure 4a, with the growth of IIA from 2001 to 2011, we observed a descending trend in the efficiency scores. This decreasing trend would be impacted by the excessive and fast-forward investments toward engaging with the growth of service and an increase in the number of connections with other airports to become one of the most important Asia-Pacific hub airports. Moreover, from 2007 to 2009 (similar to the other developed economies), South Korea was also impacted by the global economic recession, which influenced the tourism industry and businesses abroad, consequently reducing the number of aircraft movements. However, after 2011, the efficiency showed a considerable growth trend until 2019. With the worldwide expansion of the pandemic, aeronautical efficiency has declined. This phenomenon occurred after the travel ban was admitted from major hub airports in the world, including the IIA. A surprising impact of policy shifts from concentration on passenger aircraft movements to cargo aircraft movements during the pandemic is observable in the trend of the volume of cargo and the number of cargo aircraft movements. Indeed, it is possible to state that this strategy attempted to employ the available potentials of IIA during the pandemic. Figure 5 clearly shows that in the 4th quarter of 2021, the number of cargo aircraft movements was recorded as 26,054, which experienced a considerable growth of 185.8% from the 4th quarter of the year 2019. The minimum efficiency for aeronautical activities was observed in the 4th quarter of 2021, with a score of 0.76.
Figure 4. Scatter plot and smooth line of efficiency scores for the aeronautical and non-aeronautical activities. (a) Efficiency change of aeronautical activities; (b) Efficiency change of non-aeronautical activities.

Figure 5. Trend in passenger and cargo aircraft movements.

Figure 4b shows the efficiency change in IIA’s non-aeronautical production. Thus, from 2001 to 2010, we observe considerable growth in efficiency; however, after 2010 and up until 2013, there is a decreasing trend in the efficiency level. The trend of efficiency slightly improved until 2019; however, with the pandemic, once again, the efficiency scores declined dramatically. Except for the pandemic era, the fluctuations in the efficiency of the non-aeronautical production process would be an outcome of the growth of investment in this subsection of IIA (such as duty-free areas, restaurants, shops, and so forth in the second terminal) besides world economic trends. In general, it is possible to state that the aeronautical production process, with an average of 0.96 and a median of 0.98, is considered as a high-efficiency production process from 2001 to 2021 for IIA.

The endogeneity issue among input/output variables and the system of equations to measure performance measures pose a significant problem, which becomes more significant when stochastic models such as SFA are employed [88]. However, following [89], we examined our dataset and the efficiency measures by Pearson’s correlation to observe the severity of endogeneity, which was not strong. For the space constraints, we omitted the
To observe the variation of average efficiency across the pre- and post-pandemic era, we investigated the results of efficiencies for both aeronautical and non-aeronautical activities. Figure 6a indicates an average efficiency of 0.97 for aeronautical activities during the pre-pandemic era. However, IIA experienced a more than 10% drop during the post-pandemic era to an average of 0.87. The $t$-test result between the efficiency scores among the pre- and post-pandemic era was measured at 3.6, which indicated that the difference in average efficiency between these two periods was severe and at a 1% significance level. However, considering non-aeronautical activities, Figure 6b indicates an 8% decline in the average efficiency between the pre- and post-pandemic era. Here, the $t$-test also showed a result of 3.3 at a 1% significance level. The results clearly show a considerable decline in average efficiency during the post-pandemic era for both aeronautical and non-aeronautical activities.

Figure 6. Boxplot of efficiency for the aeronautical and non-aeronautical activities: (a) Pandemic era for aeronautical activities; (b) Pandemic era for non-aeronautical activities.

4.2. Tobit Regression Analysis

The application of a two-stage analysis using NDEA and Tobit models in the aviation ecosystem has been observed in several studies [39,50,68]. To evaluate the effect of some influencing factors related to the Korean aviation ecosystem on IIA efficiency, we applied a Tobit regression analysis. To justify the application of the Tobit model, Figure 3a clearly shows that the density of efficiency scores is censored to the right (very close to unity). In this situation, it is necessary to employ the Tobit model instead of the regular OLS models for the second-stage analysis. The independent variables employed for the Tobit analysis were collected directly from the IIA (2001–2021), and the dependent variable is the global efficiency scores resulting from our NDEA model for the aeronautical production process. Since we employed various independent variables in the Tobit regression analysis, the forward stepwise selection method was used to determine the most appropriate model for the second-stage assessment. Thus, nine models (including the full variable model) were created with similar characteristics to utilize the forward selection method, and the optimal model was selected among the models using the log-likelihood ratio test. The estimated results for each model are presented in Table 3. Based on the log-likelihood ratio test for the nine models, Model 7 was selected as the most suitable to explore the effect of environmental variables on the IIA efficiency. We also tested the multi-collinearity among independent variables and we did not identify any significant level in this respect.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model: Full</th>
<th>Model 1:</th>
<th>Model 2:</th>
<th>Model 3:</th>
<th>Model 4:</th>
<th>Model 5:</th>
<th>Model 6:</th>
<th>Model 7: Selected</th>
<th>Model 8:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>−5.723 *** (1.719)</td>
<td>0.972 *** (0.004)</td>
<td>1.259 *** (0.192)</td>
<td>0.767 ** (0.234)</td>
<td>−3.642 *** (0.941)</td>
<td>−5.229 ** (0.930)</td>
<td>−5.469 *** (0.945)</td>
<td>−5.183 ** (1.744)</td>
<td>−5.594 ** (1.719)</td>
</tr>
<tr>
<td>Pandemic era</td>
<td>−0.98 ** (0.066)</td>
<td>−0.079 *** (0.015)</td>
<td>−0.070 *** (0.016)</td>
<td>−0.060 *** (0.016)</td>
<td>−0.102 (0.058)</td>
<td>−0.013 † (0.035)</td>
<td>−0.0157 ** (0.040)</td>
<td>−0.454 ** (0.044)</td>
<td>0.020 * (0.051)</td>
</tr>
<tr>
<td>Log-Import (USD)</td>
<td>0.048 (0.058)</td>
<td>−0.016 † (0.010)</td>
<td>−0.042 ** (0.014)</td>
<td>0.0617 (0.042)</td>
<td>0.030 (0.037)</td>
<td>0.085 ** (0.033)</td>
<td>0.039 *** (0.047)</td>
<td>0.036 * (0.049)</td>
<td></td>
</tr>
<tr>
<td>Log-Export (USD)</td>
<td>0.252 ** (0.080)</td>
<td>0.049 * (0.198)</td>
<td>0.179 ** (0.056)</td>
<td>0.273 *** (0.055)</td>
<td>0.271 *** (0.054)</td>
<td>0.171 ** (0.062)</td>
<td>0.263 *** (0.068)</td>
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</tr>
<tr>
<td>Connectivity</td>
<td>0.010 ** (0.002)</td>
<td>0.001 (0.001)</td>
<td>0.006 *** (0.001)</td>
<td>0.115 *** (0.001)</td>
<td>0.102 *** (0.002)</td>
<td>0.006 *** (0.002)</td>
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</tr>
<tr>
<td>Airlines</td>
<td>−0.010 *** (0.002)</td>
<td>−0.006 *** (0.001)</td>
<td>−0.014 *** (0.002)</td>
<td>−0.012 *** (0.002)</td>
<td>−0.013 *** (0.003)</td>
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</tr>
<tr>
<td>Log-LCC Pax</td>
<td>−0.045 (0.035)</td>
<td>−0.014 ** (0.005)</td>
<td>−0.622 *** (0.160)</td>
<td>0.033</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Log-LCC Cargo</td>
<td>0.011 (0.038)</td>
<td>0.839 *** (0.209)</td>
<td>0.041 (0.034)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Log-Local passengers</td>
<td>0.083 † (0.049)</td>
<td>0.072 (0.047)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-Int. Passengers</td>
<td>−0.025 (0.038)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log (scale)</td>
<td>−3.607 *** (0.114)</td>
<td>−3.17 *** (0.081)</td>
<td>−3.018 *** (0.081)</td>
<td>−3.229 *** (0.082)</td>
<td>−3.418 *** (0.114)</td>
<td>−3.557 *** (0.114)</td>
<td>−3.570 *** (0.114)</td>
<td>−3.572 *** (0.114)</td>
<td>−3.601 *** (0.114)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>82.96</td>
<td>127.7</td>
<td>128.9</td>
<td>131.8</td>
<td>75.16</td>
<td>81.00</td>
<td>81.58</td>
<td>81.60</td>
<td>82.74</td>
</tr>
</tbody>
</table>

Significance codes: *** \( p < 0.001 \), ** \( p < 0.01 \), * \( p < 0.05 \), † \( p < 0.1 \).

The results show that the pandemic era (dummy variable) negatively impacts the level of IIA efficiency, and the coefficient is significant and strong. Therefore, in addition to the \( t \)-test formerly explained in Section 4.1, once again these results signified the negative impact of pandemics on airport efficiency. Imports and exports also play a significant role in improving the efficiency of aeronautical efficiency. However, exports show a sharper result, with a higher coefficient. Connectivity with other airports shows positive and significant results. Considering the number of airlines supported by IIA, the findings showed that increasing the number of airlines has a negative and significant effect on the efficiency level. A similar condition existed for the number of passengers, which were categorized as LCC pax. In contrast, the findings revealed a significant and positive coefficient when focusing on the volume of LCC cargo services.
5. Conclusion and Policy Implications

This study investigated changes in efficiency of aeronautical and non-aeronautical activities during the 20 years of IIA’s lifetime. We employed the NDAE model, using a set of desirable and undesired inputs/outputs, and assessed the dataset using window analysis. Subsequently, we employed a Tobit regression analysis to observe the impact of some internal/external independent variables on IIA efficiency.

The investigation on the dataset showed a significant drop in variables such as passengers served, passenger aircraft movements, as well as aeronautical and non-aeronautical revenues during the COVID-19 era. The same situation was observed for the undesirable variables. Surprisingly, considerable growth was found for the cargo outputs, including the volume of cargo and cargo aircraft movements for the same period. We did not identify significant changes among input variables during the COVID-19 era. Therefore, we refer to the reasons for the descending trend of efficiency scores by reflecting the negative rate of change in the annual average of some output observations from 2019 to 2021. However, it is noticeable that concentrating on cargo activities had mitigated the drastic decline in the efficiency of aeronautical activities during the COVID-19 era considerably.

The findings of efficiency estimates showed that aeronautical activities revealed a high level of efficiency within the scope of this study. The results showed that, during the development process, the level of overall efficiency deteriorated rapidly; however, these temporary negative effects of investments would be substituted by the additional value added gained from rapidly increasing the number of services to the passengers and cargo. Moreover, although the outbreak of pandemic diseases such as COVID-19 can negatively affect the performance of whole aviation systems, including IIA, implementing appropriate strategies, such as the temporary shifting from passenger services to concentrating more on cargo, would mitigate this negative impact on the efficiency level. Due to being a customer-based production model in commercial activities, the COVID-19 pandemic impacted this section more than the aeronautical production model. These results suggest that this section of IIA must be reconsidered to employ more hidden potentials to mitigate the risk of loss in capital and efficiency levels during critical situations such as the COVID-19 pandemic. Regardless of the impact of COVID-19 on the efficiency of both aeronautical and non-aeronautical activities, in general, it is possible to state that aeronautical activities performed better. However, it is notable that IIA has been considered one of the top international airports with a high performance level for commercial activities, and the findings of this study only compared the different windows of time of this organization and did not compare the efficiency level with the other airports. The t-test results indicated a significant drop in the average efficiency for both aeronautical and non-aeronautical activities by transition into the post-pandemic era.

Based on the findings of the second-stage analysis using the Tobit model and in terms of policy implications, this study offers a clear understanding of the variables that affect IIA efficiency. This could assist managers and policymakers in understanding appropriate pathways for improving the efficiency of not only the IIA, but also other airports [37,38]. The main policy implications of this empirical study are as follows: (a) outbreak of diseases such as COVID-19 would dramatically impact the aviation systems, and IIA, as one of the main infrastructures of this system in Korea, would lose its efficiency rapidly. Therefore, policymakers in health and aviation systems need to implement a set of policies to increase the speed of crisis management and its related protocols during the pandemic era, aiming to mitigate the risk and decrease the destructive effects of these phenomena on aviation systems. (b) Focusing on import and export activities would improve the efficiency of airports; however, the results showed that exports have a higher impact than import activities. Although the share of LLC cargoes is very limited, the concentration of LCC cargo services can play a significant role in improving the IIA efficiency level, which should be considered in future improvements. Furthermore, the results showed that during the COVID-19 pandemic, the IIA focused on the growth of the number of cargo movements. This strategy assisted the entire aviation system, specifically IIA, to avoid a drop in the level
of efficiency and also employing the available competency of this infrastructure during the pandemic. (c) Increasing the connectivity between the IIA and other airports (including domestic or international) would improve the efficiency of this airport. (d) Although the evidence from concentrating on increasing the number of supporting airlines and LCC passengers might affect the IIA airport efficiency in a slightly negative manner, focusing on expansion strategies of these factors would be inevitable for most air transport systems. Indeed, concentrating on LCC activities would assist airports such as the IIA in expanding their share in the domestic and international aviation market. Thus, we suggest that strategies to increase further LCC customer services in IIA must be considered cautiously and are not ignorable.

Although this study assessed the IIA efficiency, several limitations remain. First, as stated earlier in the data subsection, we only considered IIA in this study. This strategy was chosen to address the efficiency change in the dominant airports in Korea. Moreover, the homogeneity in the dataset, in addition to the unavailability of targeted variables for the other Korean airports, were the key reasons that forced us to select IIA as the only organization in this study. Second, the sample data we selected for this study only assessed a limited period of the COVID-19 pandemic, and this should be expanded in future research. Therefore, we had to employ the current time window of 2 years of pandemics for this study. Prolonging the study period would also enable us to explore this phenomenon better in future research. Third, as we stated earlier, the inconsistency and unavailability of some parts of data, such as current assets, forced us to employ the fixed assets (as a proxy of capital stock) instead of total assets in this study.

Finally, whilst the utilization of the two-stage analytical approach using DEA, SFA, and Tobit models is popular among researchers, few studies such as [90] demonstrated that two-stage methods used to predict inefficiency might have some drawbacks. However, it is noticeable that these studies mainly had utilized econometrics models such as SFA for the first stage of analysis and not DEA models. Therefore, further efforts using other methods can be helpful to identify the possible biases of the second stage’s results of this study. Some novel econometrics models such as the single-stage dynamic frontier estimation [91] are suggested to be perused in future studies. We are grateful to an anonymous referee for this invaluable comment, which we can investigate for further research.

Author Contributions: Conceptualization, M.S., Y.P. and O.K.K.; methodology, M.S.; software, M.S.; validation, Y.P. and O.K.K.; formal analysis, M.S.; investigation, M.S., Y.P. and O.K.K.; resources, J.H.C. and Y.P.; data curation, J.H.C. and M.S.; writing—original draft preparation, M.S.; writing—review and editing, M.S. and O.K.K.; visualization, M.S.; supervision, O.K.K.; project administration, O.K.K.; funding acquisition, O.K.K. and Y.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by BK-21 project entitled “Logistics Education Research Center for Resolving Social Gap in the Era of Digital Transformation”, Inha University, Graduate School of Logistics grant number INHA-64555.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

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