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Do airport environmental regulations distort aircraft allocation?: An approach based on environmental efficiency *

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Abstract

Airports and governments pursue control of the negative externalities from aircraft operations, such as noise and local air pollutants, through environmental regulations (e.g., charging or limiting). While such environmental regulations at an airport can improve the environmental performance at that airport, they may distort aircraft allocation and compromise the overall performance of the airport system. This paper proposes an approach based on environmental efficiency values measured by data envelopment analysis to assess this potential. Specifically, we estimate the environmental efficiency by employing measures of negative externalities that capture the aircraft's performance. We then regress the efficiency values on airport characteristics that indicate whether the airport should be eco-efficient. We apply the proposed approach to Japanese airport data. Our results suggest that the allocation of aircraft in Japan is not distorted in terms of negative externalities and that environmental regulations at airports in Japan may be justified.

Keywords: Airport; Environmental efficiency; Noise; Local air pollutants; Aircraft allocation

1 Introduction

Civil aviation is one of the fastest-growing industries in the global economy. As the industry grows, so does public concern about the environmental impacts of aircraft operations or negative externalities in the aviation industry. Two important negative externalities in airport areas are noise and local air pollutants. Since it is essential to understand the magnitude and properties of these environmental impacts to develop and evaluate an environmental policy, several studies have estimated the social cost of transport (Nelson, 1980; Schipper, 2004; Dings et al., 2003; Bickel and Friedrich, 2005; INFRAS/IWW, 2004; Lu and Morrell, 2006; Lu, 2009).

As manufacturers have developed new aircraft and engines with new technologies, the negative externalities per aircraft have gradually decreased; however, not all aircraft have the latest technology, implying that aircraft in use today have a variety of emission capabilities. To control negative externalities in airport areas, airports and governments have introduced environmental regulations (e.g., charging for these externalities or limiting operations by aircraft that do not conform to their standards) to encourage environmentally friendly decisions by airlines. For example, the European Commission approved the "Environmental Noise Directive," which requires member states to produce noise maps and action plans at major airports every five years. As a result, noise performance at major European airports has improved from 2006 to 2011 (Voltes-Dorta and Martín, 2016).

In Japan, the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT) proposed a guideline for environmentally friendly airports (Eco-Airport Guidelines) in 2003. Based on these guidelines, each airport (including private airports) has set up a committee (Eco-Airport committee) comprising the airport, airlines serving that airport, and local governments in that area, and each committee has its plan for airport environmental improvement. Consequently, cases exist where some airports have adopted an environmental regulation scheme while other airports have not. For example, Itami Airport (ITM) introduced a strict noise charge, Haneda Airport (HND) adopted a moderate noise charge, and Kansai International Airport (KIX) has not imposed a noise charge.

Implementing environmental regulations at an airport can improve its environmental performance, which is desirable for society; however, it may have unintended effects of compromising the environmental performance at other airports and distorting the overall performance of the airport system. Specifically, airlines may reallocate aircraft with poor environmental performance (i.e., noisy and high-emission aircraft) to airports with no or weak regulations to concentrate aircraft with good environmental performance to airports with strict regulations, resulting in worse environmental performance at airports with no or weak regulations.

The economics literature has studied these unintended effects of introducing environmental regulations. For example, empirical evidence shows that the US Clean Air Act and its amendments from 1970 have caused a relocation of polluting industries due to non-uniformity in regulatory intensity among US counties (Becker and Henderson, 2000).[1] Tanaka et al. (2022) refer to these unintended effects of environmental regulation as "displacement effects."[2]

To determine if an unintended effect arises in airport systems where environmental regulations have been introduced, we observe aircraft allocation due to environmental regulations at airports. For example, in Japan, Narita Airport (NRT) is located in the suburbs of the Tokyo metropolitan area and has limited its opening hours due to opposition from residents over noise concerns. As a result, some airlines have reallocated their aircraft to Haneda Airport (HND), which has fewer noise concerns due to its coastal location (Dobruszkes et al., 2021). Additionally, Itami Airport (ITM) is located in the center of the Osaka metropolitan area and has limited the use of jet aircraft to about half of its slots (200/370 times per day) for noise control.[3] Consequently, some routes from Itami Airport (ITM) have been reallocated to depart from the nearby Kansai International Airport (KIX) or Kobe

[1] Becker and Henderson (2000) and Hanna (2010) study the effect of the Clean Air Act and its amendments from 1970 in the US. Becker and Henderson (2000) find relocation of polluting industries across regions within the US, and Hanna (2010) shows that the amendments caused regulated multinational firms to increase their foreign output. Chung (2014) examines the pattern of foreign direct investment (FDI) of Korean companies, showing that foreign countries with weak environmental regulations attract more FDI in polluting industries than in non-polluting industries. Tanaka et al. (2022) document the impacts of tightening the US air quality standard for lead in 2009. Specifically, they show the relocation of recycling activities of used lead acid batteries from the United States to Mexico, where the air quality standard for lead remained stable after 2009. More empirical evidence is presented by Copeland and Taylor (2004) and Dechezleprêtre and Sato (2017).

[2] The economic literature has focused on the reallocation and relocation itself caused by environmental regulation. When we use the term unintended effects of environmental regulation, it includes not only the reallocation itself but also the negative effects of the environmental regulation at an airport on the other airport and airport system caused by the aircraft reallocation.

[3] In recent years, Itami Airport (ITM) has gradually relaxed the regulation and expanded the slots available for jet aircraft with low-noise. From 2012 to 2015, 85 propeller aircraft slots were progressively replaced by low-noise jets.

Airport (UKB). We must ask if such aircraft allocation resulting from environmental regulations can unintentionally affect and distort the airport system's overall environmental performance.

This paper investigates the potential for unintended effects in a national airport system. Specifically, we first employ the data envelopment analysis (DEA) approach to assess environmental efficiency. We then apply the efficiency as a dependent variable in the second-stage regression analysis to examine whether the aircraft allocation is distorted. To assess the environmental efficiency, we implement measures of two negative externalities (i.e., noise and local air pollutants) into the DEA model as undesirable outputs of airport production activities. While previous studies have proposed some methods of measuring negative externalities, we follow Grampella et al. (2017). Furthermore, since we implement undesirable outputs into the DEA model, we utilize the directional distance function (DDF) approach, allowing us to measure the distance between the frontier of a production possibility set and a point in the set with an arbitrary direction. Specific properties of the negative externality measures and the use of DDF enable us to identify airports where aircraft with high noise and high emissions operate as inefficient ones in the DEA, as detailed in subsection 3.2.3.

Next, to examine whether the aircraft allocation is distorted, we propose to regress the efficiency values on airport characteristics that indicate whether the airport should be environmentally efficient. We then observe whether the coefficient has an appropriate sign. Specifically, we focus on the two airport characteristics: airport operating hours and offshore airport. Since aircraft noise is considered to have a more significant impact on human health at nighttime than daytime, we expect airports with longer operating hours to operate aircraft with lower noise. We also conjecture that the negative impacts on human health of operating eco-inefficient aircraft at offshore airports are smaller than at other land-based airports because of the small population in their vicinity. Suppose environmental regulations at airports distort airlines' incentives, causing them to relocate eco-inefficient aircraft to airports with no or relatively weak regulations. In that case, the coefficients from the second-stage regression might demonstrate an unintended sign (e.g., offshore airports positively affect efficiency).

We apply our approach to a study of aircraft allocation in the Japanese aviation market, utilizing data from 23 major Japanese airports for 2017–2019. The data is appropriate for our analysis because it has within-sample variation in operating hours and includes four of the few offshore airports worldwide. We show that airports with longer operating hours have higher efficiency values, while offshore airports have lower efficiency values. Our results suggest no distortion in aircraft allocation in Japan regarding negative externalities. Furthermore, environmental regulations at airports in Japan may be justified.

The remainder of this paper is organized as follows. Section 2 summarizes the literature with particular attention to airport efficiency measurement studies with undesirable outputs to clarify the differences between this paper and previous studies. Section 3 describes our methodology, and Section 4 presents the data employed in our analysis. Section 5 shows the estimation results, and Section 6 concludes the paper and identifies topics for future research.

2 Literature Review

This paper's contribution relates to previous studies that measure airport efficiency with undesirable outputs. Most typically conduct a second-stage regression analysis to investigate the relationship between airport characteristics and measured efficiencies. This stream of literature is commonly interested in the difference in results with and without considering undesirable outputs.

Yu (2004) and Yu et al. (2008) measure the efficiency of Taiwan's airports with and without noise fees as an undesirable output. The latter investigates the annual productivity growth in Taiwan's airports using the Malmquist index and shows that ignoring the noise in efficiency measurement generates seriously biased growth rates. Pathomsiri et al. (2008) incorporate the number of delayed flights in their efficiency measurement of 56 US airports as an undesirable output. Their finding is that small and less congested airports are efficient when considering the delay, but it is not the case when ignoring it. Martini et al. (2013) and Scotti et al. (2014) consider several undesirable outputs generated by airports' production activity: noise and local air pollutants for the former and in addition to the two variables, delay for the latter. Both studies conduct a second-stage regression analysis to estimate the impact of various airports' characteristics on efficiency and thereby stress that the impacts change depending on whether efficiency scores are estimated with or without undesirable outputs. Fan et al. (2014) employ a DEA model with flight delays as an undesirable output for considering the quality of airport operation since flight delays seem to be one of the primary sources of customer complaints in China.[4]

For the following reasons, these previous studies have focused on the difference in results with and without considering undesirable outputs. First, ignoring undesirable outputs may lead to an unreasonable evaluation of airport efficiency. For example, suppose aircraft delays are not incorporated into the evaluation. In that case, the efficiency of congested airports (i.e., low-quality airports) may be overestimated since high production may be achieved because of the expense of quality rather than high efficiency. Second, biased efficiency could lead to biased effects in a second-stage regression. The benchmarking literature has investigated what factors contribute to an efficient airport, that is, efficiency drivers. The efficiency drivers presented by previous studies—derived from measured efficiency ignoring undesirable outputs—may not be appropriate. Therefore, it should provide implications for airport policy development to confirm whether the empirical findings in the literature are robust by comparing the efficiencies with and without undesirable outputs.

Rather than comparing the results with and without undesirable outputs, Voltes-Dorta and Martín (2016) show the improvement in noise efficiency in representative European airports between 2006 and 2011. Their choice of noise measure (55 dB Lden contour area) reflects noise abatement procedures conducted in airports, such as preferential runways or runway split. The improvement result shows that environmental regulations effectively reduce the noise produced at major airports in the EU. They also conduct a second-stage analysis of the relationship between noise abatement procedures and noise efficiency. Our study shares a common methodology with the literature, but the objective differs significantly; we explore the allocation of aircraft in a national airport system

[4]Traditional efficiency measurement with desirable output cannot capture the quality of the airports' service. This is also pointed out in Scotti et al. (2014).

as a whole rather than potential determinants of efficiency.

This paper is also related to previous studies on measuring the efficiency of Japanese airports. Yoshida and Fujimoto (2004) explore the possibility of overinvestment by regressing the efficiency on a dummy variable representing airports suspected of being constructed for political reasons. Yoshida (2004) shows lower efficiency at regional airports in Japan. Additionally, Barros et al. (2010) estimate the productivity growth of Japanese airports in 1987–2005. Ha et al. (2013) find an inverse U-shaped relationship between airport efficiency and downstream airlines' market concentration with a sample of eleven major airports in Northeast Asia, including four Japanese airports. Recently, Liu et al. (2021) explored the impact of competition between air and high-speed rail on the efficiency of Japanese airports.[5] None of these studies consider any undesirable output for efficiency measurement for Japanese airports; to the best of our knowledge, this paper is the first attempt to measure the efficiency of Japanese airports with undesirable outputs.

The literature review shows that the contribution of this paper is two-fold. This paper is the first study to propose that environmental efficiency can be applied to evaluating aircraft allocation. This research is also the first to estimate the efficiency of Japanese airports, considering undesirable outputs (noise and local air pollutants).

3 Methodology

This section introduces a method to investigate the distortion in aircraft allocation in a national airport system. First, we estimate airport efficiency using DEA, a nonparametric technique for efficiency measurement, where the two negative externalities of noise and local air pollutants are implemented into the DEA model as by-products of airport production activity, i.e., undesirable outputs.[6] This paper refers to the efficiency measured with undesirable outputs as environmental

[5] Oum et al. (2013) and Ha et al. (2017) estimate social efficiency (i.e., efficiency with CO_2 emission as an undesirable output) for Japanese airlines, rather than Japanese airports.

[6] Another approach to model negative externalities in a DEA model is to deal with these as bad inputs. This approach is discussed in Liu et al. (2010); however, we are unaware of this approach in the airport benchmarking literature.

efficiency. More specifically, we follow Färe et al. (1989); Chung et al. (1997); Färe et al. (2007) to incorporate undesirable output in the DEA efficiency measurement. We assume weak disposability for undesirable outputs and use the DDF to measure efficiency. Second, a Tobit model is estimated where the measured environmental efficiency is the dependent variable. Interpreting the environmental efficiency and the regression coefficients relies heavily on the measure of negative externalities; therefore, it is explained after the description of the measure.

3.1 Efficiency measurement and second-stage regression analysis

DEA is a method of measuring efficiency by constructing a production possibility set (PPS) from the production data of several decision-making units (DMUs) (i.e., airports) and measuring the distance between the production point of each DMU and that set's frontier.

The first step of the approach is to define the PPS. Let $x \in \mathcal{R}_+^N$ be a vector of N inputs, $y \in \mathcal{R}_+^M$ be a vector of M desirable outputs, and $b \in \mathcal{R}_+^I$ be a vector of I undesirable outputs. The PPS is given by:

$$P(x) = \{(y, b) \in \mathcal{R}_+^{M+I} | \, x \text{ can produce } (y, b)\}, x \in \mathcal{R}_+^N.$$

The set collects all the combinations of y and b that can be produced from a specific input vector x. To characterize the production technology with undesirable outputs well, the PPS should satisfy the following six axioms suggested by Färe et al. (1989).

1. Inactivity: $(0, 0) \in P(x), \forall x \in R_+^N$. It is possible to produce nothing with any inputs.

2. Compactness: $P(x)$ is a compact set. Only a finite production is possible for both desirable and undesirable outputs.

3. Strong disposability of inputs: $x' \leq x \Rightarrow P(x') \subset P(x)$. DMUs can produce the same amount of outputs with more inputs.

4. Weak disposability of outputs: $(y, b) \in P(x)$ and $\theta \in [0, 1] \Rightarrow (\theta y, \theta b) \in P(x)$. Given any inputs, a proportional reduction in both desirable and undesirable outputs is feasible.

5. Strong disposability of desirable outputs: $(y, b) \in P(x)$ and $y' \leq y \Rightarrow (y', b) \in P(x)$. DMUs can produce a less amount of desirable outputs with the same inputs.

6. Null jointness: $(y, b) \in P(x)$ and $b = 0 \Rightarrow y = 0$. When a positive amount of desirable outputs are produced for any inputs, a positive amount of undesirable outputs are also produced.

Axiom 1, 2, and 3 are standard for DEA. Färe et al. (1989) explain the standard axiom of strong disposability of outputs, $(y, b) \in P(x)$ and $(y', b') \leq (y, b) \Rightarrow (y', b') \in P(x)$, is not necessarily appropriate with the presence of undesirable outputs. Therefore, we assume weak disposability of outputs (axiom 4) with strong disposability of desirable outputs (axiom 5).

When undesirable output occurs, the standard output-oriented DEA measure—which considers the maximum proportional expansion of outputs—is invalid since the undesirable output should be reduced. To allow the contraction of undesirable outputs, Chung et al. (1997) propose an output-oriented DDF, defined by:

$$D(x, y, b; g_y, g_b) = \max\{\beta \geq 0 : (y, b) + \beta(g_y, g_b) \in P(x)\},$$

where $(g_y, g_b) \in \mathcal{R}^{M+I}$ is a directional vector that allows the measurement of the distance between the point in the PPS and the frontier in any pre-specified direction. Fig. 1 illustrates how the DDF measures the distance. The figure illustrates one desirable output and one undesirable output. The area bounded by the curved line and the horizontal axes is the PPS, and point A:(y, b) is a production point of the evaluated DMU. When g_y is positive, and g_b is negative, $(y, b)+\beta(g_y, g_b)$ also represents a production point where the desirable output increases and the undesirable output decreases from the original production point (y, b). When $\beta > 0$ takes a small value, $(y, b) + \beta(g_y, g_b)$ is feasible. As β grows, $(y, b) + \beta(g_y, g_b)$ goes out of the PPS. Therefore, the DDF measures the feasible simultaneous expansion of desirable outputs and contraction of undesirable goods from (y, b)

given the directional vector of (g_y, g_b). When (y, b) evaluated is on the frontier, the DDF is equal to 0, and the DMU is evaluated as efficient. Furthermore, when (y, b) is an inner point of the set, the DDF takes a positive value, and the DMU is evaluated as inefficient. For the inefficient DMU, there is room to become more efficient by increasing desirable outputs and decreasing undesirable outputs.

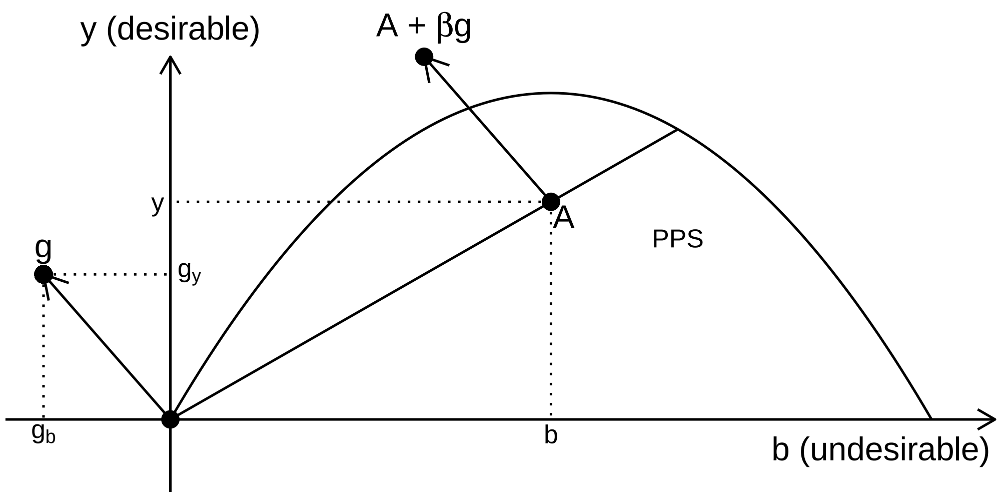

Figure 1: Production Possibility Set and Directional Distance Function

The researcher should specify the directional vector. This paper sets $(g_y, g_b) = (y, -b)$, where $(y, -b)$ is the outputs produced by evaluated DMU. In other words, we set different directional vectors for each DMU. This directional vector allows scale-free comparison among the estimated efficiency of each DMU because the DDF solves what proportions of original desirable (undesirable) outputs to be increased (decreased) to reach the frontier (Scotti et al., 2014). The environmental efficiency denoted by θ_k is estimated by calculating the DDF for all the DMUs. More specifically, we solve the following linear programming for DMU $k \in \{1, 2, ..., K\}$:

$$\begin{aligned} \theta_k \equiv D(x_k, y_k, b_k; y_k, -b_k) = \max_{\beta, \lambda} \beta & \\ \text{s.t} \quad Y\lambda \geq (1+\beta) y_k, & \\ B\lambda = (1-\beta) b_k, & \\ X\lambda \leq x_k, & \\ \lambda \geq 0, & \end{aligned} \tag{1}$$

where $X = [x_1, ..., x_K]$ denote $N \times K$ input matrix, $Y = [y_1, ..., y_K]$ denote $M \times K$desirable output matrix, $B = [b_1, ..., b_K]$ denote $I \times K$ undesirable output matrix, and $\lambda \in R_+^K$ is a weight. We use subscript k to denote a specific DMU.[7] The constraints of Eq. (1) require that a production point $(y + \beta y, b - \beta b)$ is in the PPS that is consistent with the six axioms above and derived from the production data of K DMU.

Eq. (1) indicates that we adopt the constant returns to scale (CRS) assumption concerning production technology, which is in line with previous studies using data from Japanese airports (Yoshida and Fujimoto, 2004; Yoshida, 2004; Barros et al., 2010). No consensus exists on whether to assume constant or variable returns to scale (VRS) assumptions concerning airport production activities, especially when considering negative externalities. Yoshida and Fujimoto (2004) compared the results of the CRS assumption with those of the VRS assumption and identified airports with misleading efficiency values under the VRS assumption. Therefore, we believe the CRS assumption is appropriate for the data of Japanese airports.

After obtaining the efficiency value, we conduct a second-stage analysis using a Tobit regression model of the following form:

$$\theta_k^* = z_k^T \beta + \epsilon_k, \quad \theta_k = \begin{cases} \theta_k^* & \text{if } \theta_k > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

[7]When there is no refusal, a vector is a column vector.

where θ_k^* is the latent efficiency value, θ is the efficiency measured with the DDF, and z_k is the independent variables. ϵ_k is a normally distributed error term, $\epsilon_k \sim N(0, \sigma^2)$. The independent variables z_k include potential determinants of efficiency and the variables for investigating aircraft allocation. The interpretation of the coefficient β is related to the negative externalities measure, which we explain in the last part of this section.

3.2 Measure of negative externalities

We require a measure of noise and local air pollutants to implement the two as undesirable outputs of the DEA model; noise and pollutants are not traded on the market or observed directly. Grampella et al. (2017) develop a measure of the two negative externalities: the environmental effect. They use type certification data of aircraft and engines and refer to the external cost literature; the approach calculates a monetary evaluation of externalities produced from an aircraft operation during the landing and takeoff (LTO) cycle for a specific aircraft engine combination. By aggregating the monetary evaluation regarding the number of aircraft operations at an airport in a year, the airport-year-level measure of externalities (i.e., the environmental effect) is calculated. Although they circumvent using the term "cost" to represent the measure, we use it because it is in monetized value; however, it is important to note that this measure does not correspond to the external costs incurred by noise and local air pollutants.[8]

3.2.1 Noise measure at the airport levels

The level of noise produced from aircraft operation differs between aircraft due to variances in their maximum takeoff weight, engine, or generation date of the aircraft model.[9] In other words,

[8]External costs are those incurred by residents near an airport; therefore, their estimation requires consideration of the population near the airport, its density, or even the land prices around the airport. In this sense, our measure of externalities is monetary units but not external costs. See Section 3.2.3 for more details on this distinction.

[9]The generation date of the aircraft model affects noise performance due to the improvement of technology and the noise regulation of the aircraft. The International Civil Aviation Organization (ICAO) has gradually tightened its aircraft noise standards by adopting new chapters in Annex 16, Volume I of the Convention on International Civil Aviation. Each country has enacted laws that conform to these standards, and type certification is granted to aircraft that meet the standards. The first ICAO noise standards were established in 1971, and the standards are shown in Chapter 2. In 1976, Chapter 3 standards were adopted, requiring the effective perceived noise level to be measured at

heterogeneity exists in the noise emission performance between aircraft. The first step of airport noise measurement is to obtain the aircraft level noise data.

The European Aviation Safety Association (EASA) provides data on the noise levels of different aircraft models measured at the time of type certification. Obtaining a type certificate is necessary for manufacturing an aircraft; this data covers noise performance data on aircraft operated in the civil aviation industry. During type certification, the noise level generated by an aircraft during the LTO cycle is measured in terms of the effective perceived noise level (EPNL)at three points: lateral, flyover, and approach. Considering these three measurement points, the following equation can calculate the average noise level of an aircraft:

$$\text{Aircraft\_Noise}_i = 10 \times \log_{10}\left(\frac{1}{3}\sum_q 10^{\frac{EPNL_{iq}}{10}}\right), \tag{3}$$

where $EPNL_{iq}$ represent the certified values of an specific aircraft model i at the reference point $q \in \{\text{Lateral}, \text{Flyover}, \text{Approach}\}$. Aircraft_Noise_i represents the energetic mean of the 3 certified values of an aircraft model i.

The next step is to obtain a monetary evaluation of noise produced from a single flight for all aircraft models. Schipper (2004) estimates the average external cost of noise per flight to be 324 euros (EUR) for a sample of 38 representative European airports. Grampella et al. (2017) found that the average aircraft noise level calculated by Eq. (3) was 95.3 dB in 31 Italian airports. They assigned 324 EUR for a single flight of an aircraft with a noise level of 95.3 dB, referring to the results of Schipper (2004). Furthermore, an increase (decrease) of 3 dB means the noise exposure[10] doubles (is halved). Therefore, using 95.3 dB and 324 EUR as reference values, the following formula provides the monetary evaluation per flight with an arbitrary noise level:

$$\text{Monetary\_Aircraft\_Noise}_i = 2^{\frac{\text{Aircraft\_Noise}_i - 95.3}{3}} \times 324. \tag{4}$$

three points below the standard. The new standards of Chapters 4 and 14 were adopted in 2002 and 2013, respectively. The two chapters require that the cumulative noise level, defined as the sum of noise levels at three measurement points, is below the cumulative noise level Chapter 3 permits by 10 and 17 EPNdB, respectively.

[10]The unit dB is the logarithmic relative one.

Lastly, by summing the monetary evaluation in Eq. (4) over the number of aircraft movements of each aircraft, the airport-year-level noise measure at the airport k, MAN_k[11], is calculated as:

$$MAN_k = \sum_{i \in I_k} \text{Monetary\_Aircraft\_Noise}_i \times ATM_{ki}, \tag{5}$$

where I_k represents the set of aircraft models operated at the airport k, and ATM_{ki} is the number of flights (departures and arrivals) of aircraft i at the airport k in a year. Following Grampella et al. (2017), only departure flights are considered for calculation.[12]

3.2.2 Local Air pollutants measure at the airport levels

The measure of local air pollution is calculated similarly to the noise measurements. Since air pollutants are emitted from aircraft engines, the first step in measurement is to identify the volume of pollutants emitted per LTO cycle for aircraft equipped with various types of engines.

As is the case for noise, the method of Grampella et al. (2017) uses type certificate data to identify the emission performance of engines. ICAO Aircraft Engine Emission Databank, compiled by EASA, provides certified data on the exhaust emissions of production aircraft engines. The certified data are provided according to the ICAO LTO cycle model. The model divides an LTO cycle into four phases: (i) takeoff, (ii) climb-out, (iii) approach, and (iv) idle. Emission factors (i.e., the volume of pollutants produced when an engine consumes a unit of fuel) for pollutants subject to regulation and fuel consumption are provided for each phase of an LTO cycle. Using these data, the amount of pollutant p emitted in an LTO cycle from an engine model j, denoted by

[11] MAN is the abbreviation of monetary averaged noise.

[12] Grampella et al. (2017) consider only the movements related to takeoffs in Eq. (4) (see footnote 24 on p. 335 of their paper). In other words, they assign 0 costs to arrival flights "to avoid double counting." This operation may have underestimated the noise cost MAN by half. Since Schipper (2004) estimated the unit costs per aircraft movement at the airport, we believe this operation may be unnecessary. The number of aircraft movements at an airport includes departure and arrival flights; however, this paper follows Grampella et al. (2017) to compare the results. Since this operation reduces the noise costs of the "all airports" by almost half, it does not affect the efficiency values and regression results because DEA analyzes the relative efficiency of the airport. Since this operation changes the ratio of noise cost to local air pollutants cost, the results could change when analyzing the sum of these two externalities.

Q^E_{jp} is calculated as:

$$Q^E_{jp} = \sum_f E_{jpf} \times d_f \times FC_{jf}.$$

where E_{jpf} represents the emission factor of engine model j for pollutant p during phase $f \in$ {takeoff, climb-out, approach, and idle}. d_f represents duration time, and FC_{jf} represent fuel consumption per second. This study targets several local air pollutants: hydrocarbons (HC), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and suspended particulate matter (PM_{10}).[13] Emission factors and fuel consumption are sourced from engine certification data.[14] We assume that the duration times are the same for all engines (or all flights), lasting 0.7 minutes for (i) takeoff phase, 2.2 minutes for (ii) climb-out phase, 4 minutes for (iii) approach phase, and 26 minutes for (iv) idle phase according to the definition of the ICAO LTO cycle model.

Since aircraft have several engines, the volume of pollutants emitted per LTO cycle is derived from the following equation:

$$Q_{ijp} = n_{ij} \times Q^E_{jp}$$

where Q_{ijp} is the amount of pollutant $p \in \{\mathrm{HC}, \mathrm{NO_x}, \mathrm{SO_2}, \mathrm{PM_{10}}\}$emitted in an LTO cycle from aircraft i equipped with the engine model j. n_{ij} is the aircraft's number of engines.

The next step is determining how air pollutants emitted at airports are evaluated in monetary terms. Dings et al. (2003) surveyed and integrated several European external cost studies, revealing the external unit costs of the four pollutants. They show that the unit costs of HC, NO_x, SO_2, PM_{10} are 4, 9, 6, and 150 EUR per kg of pollutants, respectively. Using these unit costs, the airport-year-level measure of local air pollutants in an airport k, LAP_k, is calculated as follows:

$$LAP_k = \sum_p C_p \times \sum_{ij} Q_{ijp} \times ATM_{ijh}, \tag{6}$$

[13]CO_2 has a global environmental impact that is not limited to an airport's surroundings; therefore, CO_2 is beyond the scope of our analysis.

[14]The emission factors for SO_2 and PM_{10} are not available for each engine because they are not subject to regulation in the type certificate. Therefore, we set $E_{j,\mathrm{SO_2},f} = 0.8(\mathrm{g/kg})$ and $E_{j,\mathrm{PM_{10}},f} = 0.2(\mathrm{g/kg})$ for all engine models j and phase f.

where C_p is the unit cost of pollutants p sourced from Dings et al. (2003). ATM_{ijh} is the number of flights of aircraft i equipped with the engine model j at airport k. Q_{ijp} contains the volume of pollutants emitted in all phases of the LTO cycle, that is, both departures and arrivals; therefore, to avoid double counting, we assume that no externality is produced when an aircraft arrives.

We require each airport's type certification data and flight-level aircraft operations data to construct the two negative externality measures. We utilize three sources: (i) the Cirium database, (ii) EASA Certification Noise level data, which we call the noise certification data,[15], and (iii) ICAO Aircraft Engine Emission Databank, which we call the engine emission certificate data.[16]

The first source provides flight-level data, including origin and destination airports, aircraft type and maximum takeoff weight (MTOW) used on the flight, and the name and number of the engine equipped. The second source provides certification data at the aircraft type level, including the aircraft type name, the MTOW of that aircraft, and its certified noise level in EPNLdB at the three measurement points. The Cirium database and noise certification data are combined using the aircraft type name and MTOW as keys. Specifically, for each combination of the aircraft type name and MTOW in the Cirium database, records with the same name and MTOW within ±3% are retrieved from the noise certification database. There are several candidate records in the noise certification data; thus, we associate the record that gives the median noise cost among the candidates. The third source provides certification data at the engine type level, including engine name, pollutant emission factor, and fuel consumption per unit of time. The emission factor and fuel consumption are certified in the four phases of the ICAO LTO cycle model. The Cirium database and engine emission certification data are combined using the engine name as the key. If several candidate records exist for the joining operation, we select the record that provides the median cost.

[15]https://www.easa.europa.eu/domains/environment/easa-certification-noise-levels

[16]https://www.easa.europa.eu/domains/environment/icao-aircraft engine-emissions-databank

3.2.3 The negative externality measure and the interpretations of the efficiency and the second-stage regression coefficients

We interpret an airport's environmental efficiency as an indicator of its operating aircraft's environmental efficiency. In other words, we identify airports with noisy and high-emission aircraft as inefficient airports in DEA. Such an interpretation is possible because of the two measures of negative externalities in Eqs. (5) and (6) have the following two properties. First, as the calculation reveals, the measures reflect the emission performance of all the aircraft operating at that airport. Suppose an airport operates noisy and high-emission aircraft. In that case, the negative externality measure of that airport takes a significant value, and the airport is evaluated as inefficient as long as the other condition, i.e., desirable outputs and inputs, are the same. Second, the measures do not reflect airport characteristics other than aircraft emission performance, such as the population surrounding the airport.

Why the two properties enable the interpretation of environmental efficiency can be clarified by analyzing a measure that does not meet the two properties, such as "external cost," and the efficiency estimated with that measure. Specifically, the external costs of noise and local air pollutants do not satisfy the second property because the estimation methods reflect the population surrounding the airport.

Previous studies have estimated the external noise costs generated around airports. These studies typically use hedonic pricing methods, where a parameter called the noise depreciation index (NDI), which represents the change in a given property value associated with a decibel change in noise exposure, is estimated by regressing housing prices or rents on a noise measure (Schipper et al., 1998). Using the NDI, the external cost generated at an airport is calculated, following Lu and Morrell (2006), as follows:

$$\sum_i NDI \times P \times (N_i - N_o) \times H_i, \tag{7}$$

where N_i represents a noise level at point i around the airport. N_o represents a background noise level, P represent average house rent around the airport, and H_i represents the number of residences at point i.

The estimation formula for the external noise cost in Eq. (7) reveals that the external costs satisfy the first property expected as a measure of externalities but not the second. To represent the level of noise exposure, N_i in Eq. (7), we use noise measures, such as the noise exposure forecast (NEF) or the day-evening-night noise level (Lden). The calculation of NEF and Lden uses EPNL—representing the noise emission performance of an aircraft—and operating data to evaluate a noise exposure for a longer period (e.g., 1 day).[17] In other words, the noise measure and the external cost are a function of the noise performance of the operating aircraft and satisfy the first property; however, the second property is not satisfied by the external cost. The calculation reflects how people around the airport evaluate noise nuisance through NDI and the population around the airport.

The population is also considered for the external cost of local air pollution. The ExternE projects, (Bickel and Friedrich, 2005), whose methods and results are cited as the most important study of external cost estimation projects, use the impact pathway approach. In this approach, a detailed model is constructed where the emitted pollutants are suspended in the air, and diffused to various areas, causing health hazards for humans. This method calculates the number of specific health hazards in each area where pollutants are dispersed so that the number of hazards is greater in densely populated areas, and the external costs are also more considerable.

Both calculations of the external cost of noise and local air pollutants consider the population's number (or density) around the airport and do not satisfy the second property. This characteristic bothers our interpretation of airport environmental efficiency, which can be clarified by considering hypothetical examples of two airports. Let the two airports have the same airport facility, be operated by the same type of aircraft fleet mix, and produce the same outputs in aircraft movements and the number of passengers; however, the two have different populations around each vicinity. When we use the external costs as undesirable outputs of the DEA model in this situation, the airport with

[17] Since EPNL measured in type certification process evaluates a noise exposure for a short period, it represents the aircraft's noise performance.

a larger population would be evaluated as inefficient since it has a higher external cost. Our study identifies airports as inefficient due to their failure to attract less noise-generating and low-emission aircraft. The example shows the inappropriateness of using the external cost. If we employ the negative externality measure in Eqs. (5) and (6), the two airports have the same efficiency value since the two have the same aircraft. The DDF with certification-based negative externality measure can identify inefficient airports when the airport is served by environmentally inefficient aircraft.

Similar to the reasoning above, noise contour data is not appropriate as a noise measure for our study. Voltes-Dorta and Martín (2016) use the area of 55 dB noise contour data—compiled as a result of "Environmental Noise Directive" in Europe—for their noise efficiency measurement. The area is affected by the fleet mix operated in the airport and other restrictions not related to the fleet mix. A preferential runway is an example. If an airport introduces a preferential runway, aircraft should circumvent densely populated areas, allowing the aircraft to take a long way around and deduce a wider area of noise contour. In particular, Voltes-Dorta and Martín (2016) show in their second-stage analysis that the preferential runway negatively impacts efficiency, which implies a broader area of noise contour. Our study is related to the airline's choice of aircraft, and this measure is also inappropriate.

Lastly, we caveat the interpretation of the regression analysis. The regression model in Eq. (2) has a variable to detect distortion in aircraft allocation. Because the environmental efficiency of an airport captures the emission performance of operating aircraft, a positive impact corresponds to the use of high-emission performance aircraft. Regressing the efficiency on variables that indicate whether the airport should be eco-efficient, we try to detect distortion in aircraft allocation in a national airport system; however, the regression results have only a screening role. In other words, if environmental regulations caused a significant distortion in aircraft allocation, the regression coefficients would display an unintended sign, e.g., the longer operating time airport has low-efficiency values; however, the absence of an unintended sign does not mean the absence of distortion. In other words, a weak distortion does not change the regression coefficient to the unintended sign. In this sense, regression is only screening.

4 Variables and data sources

We apply the approach developed in Section 3 to balanced panel data for 23 major Japanese airports from 2017 to 2019. The selection of major airports is based on the government's definition of airport classification. According to the definition, Japanese airports can be classified into three categories. The first category includes 28 airports that serve international and domestic trunk routes and are mainly administered by the central government (MLIT). The second category includes 54 airports that are responsible for regional air traffic and are administered by local governments.[18] The other 15 airports are in the third category. Our 23 sample airports are part of the first category. We exclude five airports in the first category because of their operational entity (local governments) and small size compared to the others. Although the sample construction is based on the government's definition of major airports, these airports account for a large portion of Japanese aviation and are representative airports. In 2017, Japanese airports received 312.6 million passengers and 2.16 million aircraft movements. The sample accounts for 90% for passengers (282.7 million) and 86% for aircraft movements (1.85 million).

The input and output variables for airport production activity are specified for efficiency measurement. On the output side, we consider two variables: the number of air passenger movements (APM) and the volume of cargo handled ($CARGO$). Air passenger movements include both domestic and international. Regarding input, we consider two variables: airport surface area ($LAND$) and runway length ($RUNWAY$). An airport's surface area represents its general size. The length of the runway influences the ability to accept large and long-flight aircraft, which can carry more passengers and cargo and affect the airport's production function (the frontier of PPS). In general, production activity uses capital and labor as inputs. The absence of labor-related variables for our analysis is due to data availability. Some literature on benchmarking Japanese airports uses the number of employees in terminal buildings as the labor input. (Yoshida and Fujimoto, 2004; Liu et al., 2021). In Japan, terminal buildings are operated by the private sector, and the labor

[18] Historically, the second category includes airports built partially for political reasons and deemed inefficient airports (Yoshida and Fujimoto, 2004).

variable includes those who perform airport operations and those who provide various services such as concessions, parking, and safety. Since the services provided differ between airports, the meaning of the labor variable can vary from airport to airport. Rather than using the number of employees in terminal buildings, Yoshida (2004) assumes the perfect complementarity between labor and capital. We follow this approach as it enables unbiased efficiency measurement even when omitting the labor variables. The undesirable output is the negative externality measure of MAN in Eq. (5) and LAP in Eq. (6).

Our specification of inputs and desirable outputs is a typical selection for airport benchmarking literature; we do not include any input variables to reduce undesirable outputs. When undesirable outputs are incorporated into DEA, some previous studies consider inputs that affect the production frontier for undesirable outputs. For example, Fan et al. (2014) include the number of flight delays as an undesirable output and the number of baggage claims as an input in their DEA model because the more baggage claims an airport has, the less congestion and delays it experiences. Conversely, our study calculates the negative externality measures based on the aircraft's emission performance. Emission performance varies among aircraft sizes and models in the same category. A large externality due to the fact that only disadvantaged-sized aircraft can enter the airport should not be reflected as inefficiency and should be reflected in the airport production function. Therefore, we must include input variables that capture an airport's accommodation ability.[19] Such an airport ability is reflected in production technology by including the runway length as input. Therefore, our DEA model has no input factor specific to reducing undesirable outputs.

For the second-stage of the Tobit analysis, we consider two independent variables: variables to investigate aircraft allocation and potential efficiency drivers. For the first type, we consider two variables. SEA is a dummy variable representing whether the airport is an offshore airport. Japan has five offshore airports: Nagasaki Airport (NGS), Kansai International Airport (KIX), Kobe Airport (UKB), Kitakyusyu Airport (KKJ), and Tyubu International Airport (NGO). All but Kobe Airport (UKB) are included in our 23 sample airports. $OPHOUR$ represents the operating hours

[19] An airport that can accommodate advantaged-sized aircraft but have disadvantaged-size aircraft is surely evaluated as inefficient.

of an airport and is converted into the rate by dividing 24. We expect that SEA has a negative impact and that $OPHOUR$ positively impacts environmental efficiency if aircraft allocation in the Japanese airport system is not distorted.

The other type of explanatory variable is the potential efficiency driver. The extant literature has examined the role of airport size and aircraft size as efficiency drivers (Graham, 2005). We use the number of aircraft movements (ATM) to represent airport size. Airports vary widely in size, and the effect of a unit increase in size on efficiency values is likely to differ for small and large airports; therefore, this variable is incorporated into Tobit regression in a logarithmic form. The average aircraft size used at an airport ($FLEET$) is measured as follows. First, we aggregate the maximum takeoff weight of all flights at an airport ($TOTAL\_MTOW$)[20]. Second, the average size is calculated as $FLEET = TOTAL\_MTOW/ATM$. We consider several variables that describe the managerial environment of airport operations and whose effect on efficiency has been studied in the airport benchmarking literature. The managerial environment influences an airport's production decision and operating hours, which can correlate between the operating hours and the variables of the managerial environment; therefore, we should control these managerial variables to identify the coefficient of an airport's operating hours. We include the percentage of international flights ($ISHARE$), a dummy variable that represents whether the airport is administered by a company rather than the central government ($COMPANY$), and a dummy variable representing the presence of a competitive high-speed rail station within a 40 km radius of an airport (HSR).[21] [22]

Our efficiency measurement data are constructed from several sources. The input and desirable output variables are drawn from *Airport Terminal Building Handbook*[23] published by All Japan

[20] $TOTAL\_MTOW_k = \sum_i MTOW_{ik}$, where $MTOW_{ik}$ represent the maximum takeoff weight of flight i in airport k.

[21] The effects of market structures on technical efficiencies, such as the percentage of international flights or the competition among airports, are explored in the literature (Scotti et al., 2012; Ha et al., 2013; Chow and Fung, 2009). Several contributions focus on the effect of airport governance structure on airport efficiency (Vogel, 2006; Oum et al., 2006, 2013). Recently, the possible impact of HSR on airport efficiency has been investigated by Ha et al. (2013) and Liu et al. (2021).

[22] We constructed the HSR variable with a slight modification to the model from Ha et al. (2013), which constructed a dummy variable based on whether there is a high-speed rail in the same city as the airport. With their definition, we identify airports that seem to face competition from high-speed railways but have not been identified as under competition, so we adopt the 40 km criterion.

[23] *Zenkoku Kuko Taminaru Biru Yoran* in Japanese.

Airport Association and *Airport Status Report*[24] published by MLIT, respectively. Both sources present data annually. As Section 3.2 explained, the source of constructing negative externality measures include the (i) Cirium database, (ii) EASA Certification Noise level data, and (iii) ICAO Aircraft Engine Emission Databank.

5 Empirical Analysis

5.1 Descriptive analysis

Table 1: Descriptive statistics

vars	n	mean	sd	median	min	max
RUNWAY (km)	69	3856.61	2125.34	3000.00	2200.00	11360.00
LAND (km^2)	69	366.08	374.04	198.00	99.00	1522.00
APM (thou.)	69	12414.69	18820.43	3269.49	196.64	86051.08
CARGO (thou. ton)	69	237.75	511.90	13.17	0.09	2313.75
WLU (thou.ton)	69	1479.22	2302.50	340.44	19.76	9860.48
MAN (thou. euro)	69	10630.99	15938.53	3074.14	182.62	70481.53
LAP (thou. euro)	69	8418.51	13965.71	1821.15	92.23	61463.04
TE (thou. euro)	69	19049.50	29863.83	4801.21	274.85	131944.56
SEA (dummy)	69	0.17	0.38	0.00	0.00	1.00
OPHOUR (%)	69	0.72	0.21	0.58	0.42	1.00
ATM (thou.)	69	82.56	102.93	28.57	2.28	449.24
FLEET (ton)	69	87.66	33.08	78.31	39.47	185.56
TOTAL_MTOW (thou. ton)	69	9912.37	16195.61	2236.33	127.14	70072.15
ISHARE (%)	69	0.17	0.22	0.10	0.00	0.82
COMPANY (dummy)	69	0.17	0.38	0.00	0.00	1.00
HSR (dummy)	69	0.43	0.50	0.00	0.00	1.00

We start with a descriptive analysis, focusing on two negative externalities. Table 1 presents the summary statistics. Fig 2 depicts the airport size and the amount of negative externality produced at airports on a logarithmic scale for 2017. The points have different shapes based on the airports' characteristics. A circle (square) point represents an offshore (land) airport, and a filled black (unfilled white) point represents an airport with longer (shorter) operating hours than the median.

[24] *Kuko Kanri Jokyo Chosyo* in Japanese.

Since the calculation of LAP and MAN depends on the number of aircraft movements, we observe a relationship where negative externality increases as airports size increases.

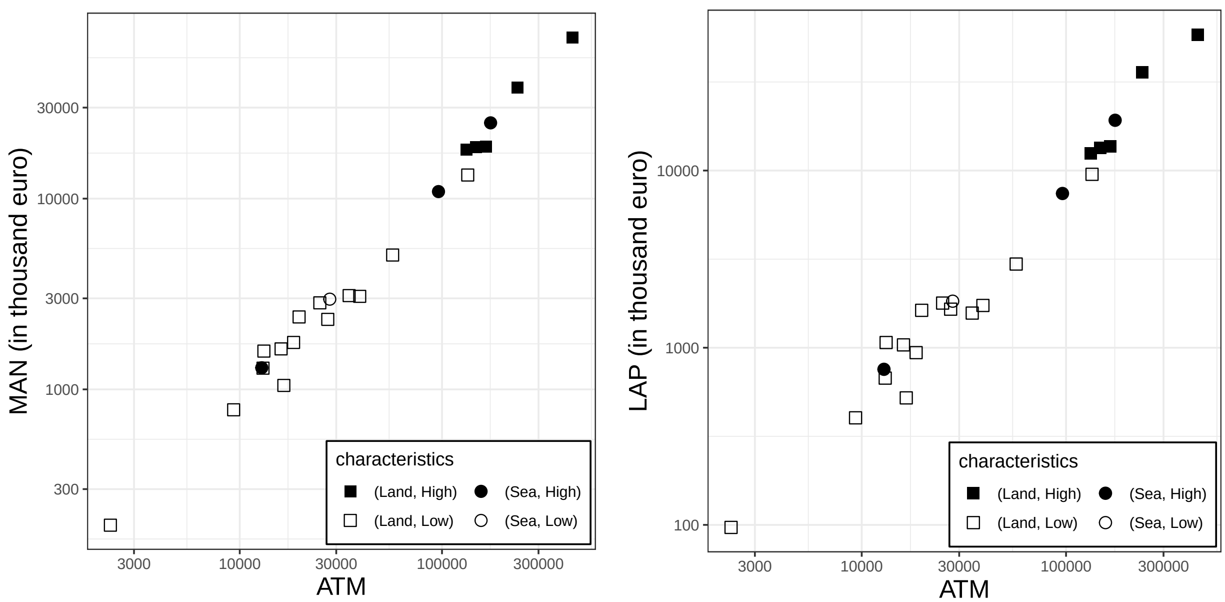

Figure 2: MAN and LAP for 23 Japanese airports in 2017

We analyze two types of average costs in Fig. 3 and 4. Fig. 3 plots the average costs per aircraft movement. The average cost is calculated by dividing the amount of externality (MAN and LAP) by the number of aircraft movements (ATM). When focusing on airport characteristics, the average cost is relatively high for offshore airports (circle points) compared with land airports (square points). Moreover, airports with longer operating hours (filled points) use aircraft with high average costs. We cannot immediately interpret the results as indicating these airports have inefficient aircraft. Most airports with longer operating hours are large and likely to operate larger aircraft; therefore, the relationship may be caused by aircraft size. That is, larger aircraft produce more negative externality for a single flight. Lastly, Fig. 4 depicts the average aircraft size and the average cost per MTOW, calculated by dividing the amount of negative externality by $TOAL\_MTOW$. The figure shows that large aircraft have an advantage regarding noise emissions but a disadvantage regarding local air pollutants.

The second-stage regression analysis in Scotti et al. (2014) and Voltes-Dorta and Martín (2016) shows that aircraft size positively impacts airport efficiency, measured with noise emission. The

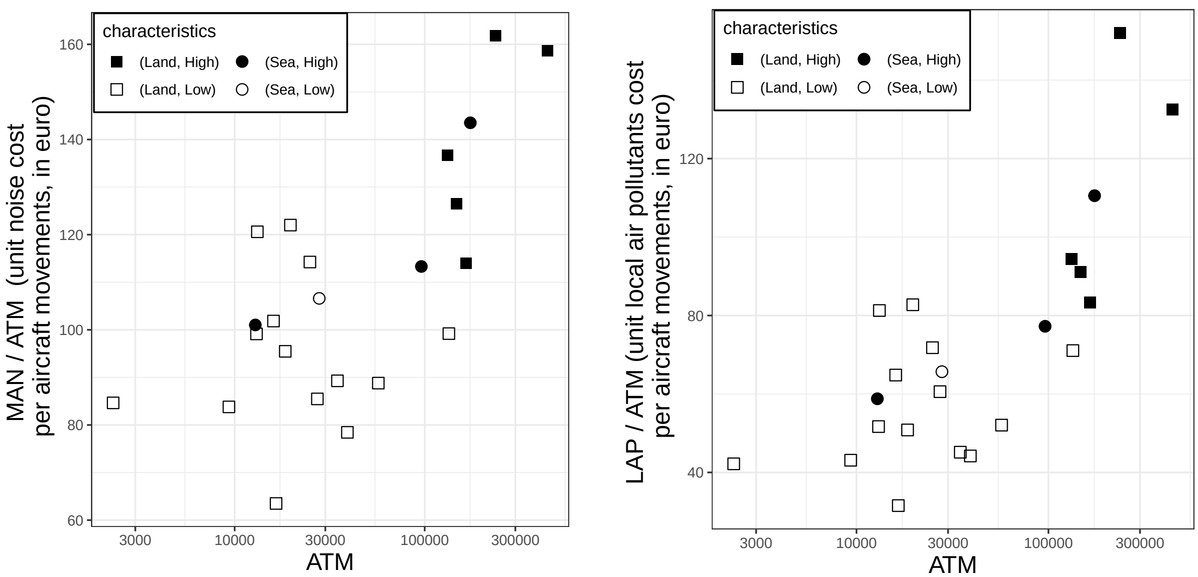

Figure 3: Average costs per aircraft movements

former also shows a negative impact of aircraft size on airport efficiency, measured with local air pollutants as undesirable outputs. Our findings on the advantages and disadvantages of large aircraft size concerning noise and local air pollutants, respectively, are consistent with their result, as shown in Fig 4.[25]

5.2 Efficiency measurement

We estimate airport efficiency under five cases of DEA models for comparison. Each case has different specifications of output variables, and all cases have the same input variables. Case 1 is our baseline specification with two inputs, $LAND$ and $RUNWAY$, two desirable outputs, APM and $CARGO$, and two undesirable outputs, MAN and LAP. Cases 2 and 3 have only MAN and LAP, respectively, as undesirable output; otherwise, they are the same as Case 1. Case 4 uses integrated output variables: work-load unit ($WLU = 0.1 \times APM + CARGO$) as a desirable output and total environmental effect ($TE = MAN + LAP$) as an undesirable output. Case 5 has no undesirable

[25] Scotti et al. (2014) also employ certification-based measures of negative externalities. The measures are slightly different from Grampella et al. (2017) and are not monetized value. Voltes-Dorta and Martín (2016) use the area of 55 Lden contour as their noise measure. Since the measures employed in the two studies are not monetized value, they do not perform a unit cost analysis.

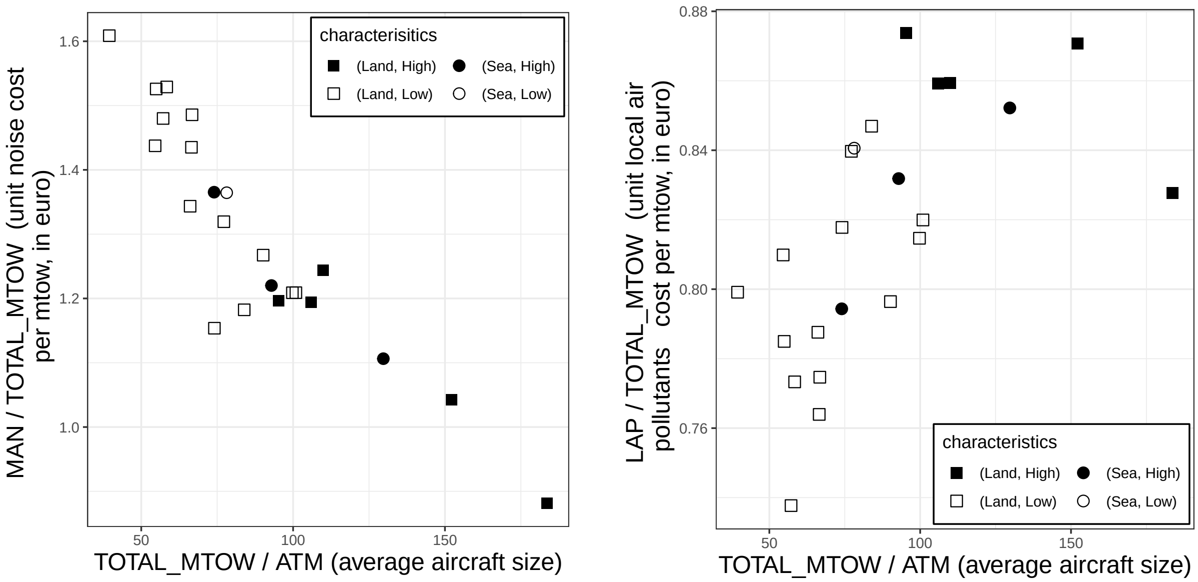

Figure 4: Average costs per maximum takeoff weights

outputs and has the same desirable outputs as Case 1. In Cases 1–4, we use the DDF to measure efficiency, while Case 5 is an ordinal output-oriented efficiency measure.

Table 2 presents the estimated efficiency with rankings and airport characteristics. The rankings vary depending on whether the two negative externalities are considered. When aircraft allocation is appropriate and offshore airports have relatively inefficient aircraft, offshore airports should have lower rankings in environmental efficiency than in technical efficiency. Chubu Centrair International Airport (NGO) and Nagasaki Airport (NGS) ranked 9th and 13th, respectively, in no undesirable output (Case 5); they were ranked 21st and 22nd, respectively, in our baseline case (Case 1). Some counter-intuitive results were observed in the ranking fluctuations. Itami Airport (ITM) is located in an urban area and has been a pioneer in reducing noise, including introducing low-noise aircraft; however, it ranked 5th in Case 5, lower in all cases that consider negative externalities (e.g., 19th for Case 1).[26] Since various airport characteristics influence efficiency, the ranking analysis is not sufficient and confusing. We rely on the Tobit regression analysis for precise analysis.

[26]Itami Airport (ITM) is similar in size to Fukuoka Airport (FUK) and ranked first among all models. Fukuoka Airport (FUK) belongs to the reference set for calculating Itami's efficiencies, making the inefficiency score of Itaimi larger and may cause the seemingly counter-intuitive result.

Table 2: Efficiency value of 23 Japanese airports for 2017 with their ranking

	CODE	SEA	OPHOUR	Case 1	Case 2	Case 3	Case 4	Case 5
1	FUK	0	1.00	0.000 (1)	0.000 (1)	0.000 (20)	0.000 (1)	1.000 (3)
2	KIX	1	1.00	0.000 (1)	0.006 (5)	0.000 (21)	0.000 (1)	1.865 (6)
3	KIJ	0	0.58	0.000 (1)	0.147 (22)	0.059 (3)	0.126 (22)	13.22 (21)
4	KOJ	0	0.58	0.000 (1)	0.071 (14)	0.000 (15)	0.061 (14)	2.246 (8)
5	MYJ	0	0.58	0.000 (1)	0.000 (1)	0.032 (11)	0.037 (8)	3.002 (10)
6	KMI	0	0.58	0.000 (1)	0.116 (20)	0.000 (9)	0.090 (18)	3.745 (12)
7	WKJ	0	0.42	0.000 (1)	0.123 (21)	0.037 (1)	0.099 (20)	33.83 (23)
8	KCZ	0	0.58	0.000 (1)	0.064 (13)	0.000 (4)	0.043 (10)	6.433 (19)
9	KKJ	1	1.00	0.000 (1)	0.013 (6)	0.000 (5)	0.008 (5)	6.530 (20)
10	NRT	0	1.00	0.000 (10)	0.000 (1)	0.000 (22)	0.000 (1)	1.000 (1)
11	OKA	0	1.00	0.000 (11)	0.000 (1)	0.000 (18)	0.000 (1)	1.000 (1)
12	HND	0	1.00	0.000 (12)	0.020 (9)	0.080 (23)	0.049 (11)	1.114 (4)
13	OIT	0	0.58	0.013 (13)	0.089 (18)	0.013 (6)	0.066 (16)	5.221 (16)
14	KMJ	0	0.58	0.013 (14)	0.050 (12)	0.023 (13)	0.052 (12)	3.047 (11)
15	CTS	0	1.00	0.016 (15)	0.017 (7)	0.023 (19)	0.035 (6)	2.115 (7)
16	TAK	0	0.62	0.016 (16)	0.020 (8)	0.060 (8)	0.043 (9)	5.241 (17)
17	HIJ	0	0.58	0.017 (17)	0.021 (10)	0.048 (10)	0.035 (7)	4.517 (14)
18	SDJ	0	0.58	0.021 (18)	0.079 (16)	0.027 (12)	0.073 (17)	4.721 (15)
19	ITM	0	0.58	0.037 (19)	0.042 (11)	0.041 (17)	0.058 (13)	1.351 (5)
20	KUH	0	0.54	0.047 (20)	0.155 (23)	0.080 (2)	0.128 (23)	14.56 (22)
21	NGO	1	1.00	0.054 (21)	0.076 (15)	0.054 (16)	0.065 (15)	2.445 (9)
22	NGS	1	0.62	0.071 (22)	0.101 (19)	0.081 (14)	0.103 (21)	4.301 (13)
23	HKD	0	0.54	0.080 (23)	0.088 (17)	0.107 (7)	0.096 (19)	6.246 (18)

5.3 Tobit analysis

The result of the Tobit regression analysis is presented in Table 3. Since both the environmental efficiency of Cases 1–4 and the technical efficiency of Case 5 are inefficiency scores, the independent variables whose coefficients are positively estimated negatively impact airport efficiency. We estimate Tobit models with and without potential efficiency drivers for all five efficiency cases; therefore, Table 3 has ten regression results.

Regarding environmental efficiencies as a dependent variable (Models 1–8), almost all models represent similar results for SEA and $OPHOUR$ variables. Models 1 and 2 are our baseline since they employ the environmental efficiency measured with the two negative externalities MAN and LAP. The coefficient of SEA is estimated to be 0.02 at the 5% significance level in Model 1, suggesting that the aircraft at offshore airports are less environmentally efficient (i.e., noisy and high-emission) than those at land airports. Moreover, the coefficient of $OPHOUR$ is estimated to be -0.04 at the 5% significance level; airports with longer operating hours can attract more environmentally efficient aircraft than those with shorter operating hours. Model 2 shows that these results remain unchanged even after controlling for average aircraft size operating in an airport. We determined that airports with longer operating hours have a high unit cost per aircraft movement, seemingly interpretable as a distortion of aircraft allocation in Fig 3; however, the regression result reveals that the more environmentally efficient aircraft are allocated to airports with longer operating hours when controlling the aircraft size. The result of higher costs at airports with longer operating hours is because of the airports' large aircraft size. These findings indicate that aircraft allocation in the Japanese airport system is not distorted from the viewpoint of negative externalities.

Concerning the control variables, only the average aircraft size ($FLEET$) have statistically significant impacts on environmental efficiency. Similar results to previous studies are observed for the impact of average aircraft size. When only noise is incorporated in efficiency measurement, the average aircraft size positively impacts environmental efficiency from Model 4. When only local air pollutant is incorporated, the average aircraft size negatively affects the efficiency indicated in Model 6. This result is in line with the regression result of Scotti et al. (2014) and the (dis) advantage of larger aircraft for noise (local air pollutants) emission observed in Fig 4. Since Scotti et al. (2014) employ a certification-based measure of negative externality, these results may be a feature of the measure.

The regression results using technical efficiency differ from the environmental efficiency results. The SEA and $OPHOUR$ have no impact on the technical efficiency. Only airport size represented by ATM has a statistically significant positive impact on efficiency.[27] The positive impact on airport size has been found in many airport benchmark ranking literature (Oum and Yu, 2004; Barros and Dieke, 2007; Barros, 2008; Tsekeris, 2011) Our results confirm these findings using

[27] The positive impact of $OPHOUR$ in Model 9 is due to the lack of ATM; an airport with longer operating hours has an opportunity to increase ATM. The two variables have a positive correlation in our data. The positive impact of ATM in Model 10 emerges as the positive impact of $OPHOUR$ in Model 9.

Japanese airport data.

Table 3: Tobit Regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
(Intercept)	0.03^{*}	-0.05	0.18^{***}	0.13^{**}	0.08^{***}	-0.01	0.16^{***}	0.07^{*}	21.36^{***}	63.97^{***}
	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)	(0.01)	(0.03)	(2.96)	(6.46)
OPHOUR	-0.04^{*}	-0.10^{**}	-0.19^{***}	-0.13^{**}	-0.09^{**}	-0.17^{***}	-0.15^{***}	-0.15^{***}	-23.91^{***}	5.27
	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.05)	(0.02)	(0.03)	(4.30)	(6.18)
SEA	0.02^{*}	0.04^{***}	0.05^{***}	0.04^{**}	0.02	0.06^{***}	0.03^{**}	0.04^{***}	4.01	-3.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(2.24)	(2.04)
FLEET		0.00^{*}		-0.00^{***}		0.00^{***}		-0.00		0.01
		(0.00)		(0.00)		(0.00)		(0.00)		(0.03)
log(ATM)		0.01		0.01		0.01		0.01^{*}		-6.01^{***}
		(0.01)		(0.01)		(0.01)		(0.00)		(0.90)
ISHARE		-0.05		0.01		-0.08		-0.04		-0.40
		(0.03)		(0.04)		(0.04)		(0.03)		(5.60)
HSR		0.00		-0.01		0.01		-0.00		-0.24
		(0.01)		(0.01)		(0.01)		(0.01)		(1.19)
COMPANY		0.00		-0.02		-0.02		-0.02		5.08^{*}
		(0.01)		(0.02)		(0.02)		(0.01)		(2.57)
Efficiency	Case 1	Case 1	Case 2	Case 2	Case 3	Case 3	Case 4	Case 4	Case 5	Case 5
log(σ)	-3.62^{***}	-3.71^{***}	-3.39^{***}	-3.53^{***}	-3.23^{***}	-3.44^{***}	-3.68^{***}	-3.78^{***}	1.82^{***}	1.49^{***}
	(0.12)	(0.12)	(0.09)	(0.09)	(0.11)	(0.11)	(0.09)	(0.09)	(0.09)	(0.09)
Log Likelihood	75.72	82.02	109.23	117.39	67.22	78.13	128.24	135.96	-204.10	-183.92
Sample Size	69	69	69	69	69	69	69	69	69	69

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

6 Conclusion

This study evaluates aircraft allocation in the Japanese aviation system from the perspective of negative externalities. Specifically, we examine whether the environmental regulations imposed by each airport negatively impact airports with no or weak restrictions, i.e., airlines engage in distorted aircraft allocation. We propose using environmental efficiency estimated with a certification-based measure of negative externalities and second-stage analysis for this purpose.

Our main results are as follows. The second-stage Tobit regression shows that offshore airports have lower environmental efficiency values, and airports with longer operating hours have higher efficiency values. Therefore, we find that the allocation of airports in the Japanese aviation system is not distorted from the perspective of a negative externality; we do not observe a distorted shift. Furthermore, we find characteristics of a certification-based measure of negative externalities and could explain the relationship between the characteristics and the regression results. We find the advantage of larger aircraft size on noise emissions, reflected in the positive effect of average aircraft size on environmental efficiency measured with noise. Similar effects are observed in the opposite direction for local air pollutants.

Our proposed method and its result have a direct policy implication. Even if an airport succeeds in reducing negative externalities, the reduction efforts may negatively impact other airports and induce a distorted aircraft allocation. Negative externalities at an airport and the airport's efforts to reduce them should not be evaluated separately but concerning other airports. Our proposed regression method allows the evaluation of aircraft allocation in a national airport system rather than in a single airport, suggesting that the efforts of individual airports and governments to improve environmental performance can be justified from a national perspective.

Finally, this study has three limitations. First, the regression method has only screening capability. If environmental regulations cause a large distortion of aircraft allocation, the regression coefficient can have an unintended sign; however, a small distortion leaves the sign of the coefficient unchanged. A method that can detect small distortions should be developed. The second limitation relates to the scope of the airport system. An aircraft not meeting the environmental standard may be sold in a second-hand market and used overseas. Since we analyze a national airport system using airport data from a single country, our proposed method cannot detect cross-country displacement. If such displacement is the subject of research, the scope of the airport system should be expanded. Finally, our measure of negative eternality and environmental efficiency only reflects the efforts of airports to encourage airlines to use environmentally friendly aircraft. In 2001, ICAO adopted a policy called the "Balanced Approach" to airport noise management, which comprises four elements to reduce noise exposure: (i) reduction of noise at source, (ii) land use planning and management, (iii) noise abatement operational procedures, and (iv) operating restrictions. However, this study only assessed airports' efforts regarding the first and fourth elements; therefore, future efficiency studies can implement measures that reflect various airport environmental efforts and regulations.

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