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Efficiency of Peruvian regional airports: Does the PPP framework make a difference?

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ABSTRACT

This paper examines whether Public-Private Partnership (PPP) frameworks have improved the technical efficiency of Peruvian regional airports. Using panel data from 17 airports between 2004 and 2017, we estimate a Latent Class Stochastic Frontier Model (LCSFM) based on an input-oriented Cobb-Douglas distance function, which is explicitly controlling for unobserved technological heterogeneity. Airports are classified into two technological groups, with concessionaire status (AdP) serving as a separating variable. Results reveal that airports managed under PPP schemes achieve higher efficiency levels and are more likely to operate with superior technology, with both groups exhibiting increasing returns to scale. Evidence of technological progress, biased towards operational expenditures, suggests that efficiency gains have been driven by labour innovations, outsourcing, and digitalization. These findings highlight the positive role of PPPs in fostering operational improvements and underline the risks of ignoring heterogeneity in regulatory benchmarking. We argue that incorporating heterogeneity-adjusted models into regulatory frameworks could strengthen incentive-based policies, guide infrastructure investments more effectively, and support sustainable development of regional air transport networks.

1. Introduction

In terms of support for the air transport sector, airports play a key role in social context and economic development around the world. This is due to the fact that airport infrastructure facilitates trade and enhances connectivity among people and countries.

Over the past three decades, the airport sector in Latin America and the Caribbean has undergone significant reforms. Market liberalization has allowed for technological improvements and greater private sector participation in airport management. Likewise, the increase in demand for air transport, driven by growth in tourism and trade, has encouraged governments to implement structural reforms aimed at improving operational efficiency and the provision of airport and aeronautical services.

Most Latin American countries have adopted public-private partnerships (PPPs), but the approaches adopted vary (individual, group and mixed), depending on the regulatory framework adopted and the economic context (Suárez-Alemán et al., 2020; Serebrisky, 2012). Some countries have chosen to grant concession airports individually, as in the case of Chile and Costa Rica. Other countries, such as Mexico and Brazil, have chosen to grant concession airports in groups. This model seeks to establish a cross-subsidy scheme between the more and less profitable airports, encouraging private investment and the integrated development of each country's airport network (Serebrisky, 2012). A third approach is the mixed model, which combines individual concessions with groups of airports, as pursued by Colombia and Peru for example. This system has allowed investment to be attracted and airport infrastructure to be improved in a balanced way (Suárez-Alemán et al., 2020; Serebrisky, 2012).

Although Peru has experienced an expansion of airport infrastructure through PPPs in recent years, regional airports, it still faces a significant infrastructure gap, and its quality remains lower compared to other countries in the region. According to the Global Competitiveness Report 2019; World Economic Forum (2019), Peru ranked 65th out of 141 countries in overall competitiveness and 50th in airport connectivity. Moreover, according to Bonifaz et al. (2020), Peru's infrastructure gap is estimated at approximately USD 730 million. Thus, the development of enhanced airport infrastructure is crucial in the Peruvian context, given the growing demand for air transport and the necessity for efficient airport infrastructure to support it. This has underscored the

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need to evaluate the effects of management practices and airport characteristics on technical efficiency.

Regarding the theoretical foundations, this study is grounded in frameworks that explain the relationship between PPPs and the efficiency with which infrastructure services are delivered. According to the economics of PPPs, private participation allows for risk sharing and creates incentives that promote cost efficiency and improved service quality (Grout, 1997). From the perspective of principal–agent theory, delegating management from the state (the principal) to a concessionaire (the agent) may introduce information asymmetries and incomplete contracts that affect performance (Laffont and Tirole, 1993). Similarly, incomplete contract theory argues that, since not all contingencies can be specified *ex ante*, the allocation of control rights becomes pivotal in ensuring efficiency incentives (Hart, 2003).

Taken together, these frameworks provide a robust theoretical foundation for understanding why PPPs can foster improvements in operational efficiency. Nevertheless, the long-term success of PPPs also depends on sound institutional mechanisms and regulatory frameworks that ensure efficiency in service provision and predictability for concessionaires, thereby reinforcing the sustainability of public–private partnerships over time.

The objective of this paper is threefold. Firstly, it aims to assess and compare the efficiency of Peruvian regional airports, in order to evaluate whether the reform process has improved the technical efficiency of regional airports. Secondly, it seeks to identify possible technological differences among these airports. To this end, an input-distance function was estimated using the Latent Class Stochastic Frontier Model (LCSFM) for a sample of 17 airports observed during the period 2004–2017. Finally, it aims to contribute to the regulatory process by providing relevant information to regulators on how to deal with heterogeneity when assessing and comparing efficiencies.

It should be noted that when evaluating and comparing efficiency, one crucial issue is the treatment of heterogeneity. If this heterogeneity exists and is not explicitly accounted for in the model, the estimated coefficients of the included variables may be biased (Chang and Tovar, 2017). In our case, this issue becomes particularly relevant due to potential differences among airports in terms of geographical location, volume of traffic, ownership structure, regulatory frameworks and other factors. Therefore, the LCSFM is used to account for possible technological differences among groups of airports.

The paper is organized as follows. After the introduction, the second section provides a comprehensive review of airport efficiency studies using Stochastic Frontier Analysis (SFA). Section 3 describes briefly the Peruvian airport sector and the reform process. Section 4 presents the methodology. Section 5 introduces the data, and the variables used to estimate the model. Section 6 contains the empirical results. Finally, Section 7 presents the main conclusions, policy implications and directions for future research.

2. Review of airport efficiency studies using SFA

There is extensive literature on performance measurement associated to airport (Bezerra and Gomes, 2016) with efficiency/productivity being predominant. When it comes to measuring efficiency and/or productivity using frontier techniques, two main approaches could be identified in the empirical literature (Liebert and Niemeier, 2013): Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). In a recent bibliometric analysis, See et al. (2023) showed that the annual growth rate of publications related to airport efficiency and productivity studies in peer-reviewed journals was 10.96 % over the last two decades.

Similarly to what happened in other infrastructure and utility industries, most of the airport efficiency/productivity studies have used DEA. The popularity of this non-parametric method is most likely due to its ability to produce results with relatively small data sets and its lack of assumptions about production technology (Tovar and Rodríguez-Deniz, 2015; Tovar and Wall, 2015). Reviews of the literature on airport efficiency using DEA can be found in Fasone and Zapata-Aguirre (2016) and Iyer and Jain (2019).

DEA and SFA techniques have advantages and drawbacks. We agree with Tovar and Martín-Cejas (2010) who believes that, when it comes to measuring airport efficiency, the advantages of SFA are clear: "*SFA allows for random unobserved heterogeneity among the different firms, for statistical inference in the significance of the variables included in the model, and finally it also allows the inefficiency effect to be separated from the statistical noise due to errors in data, omitted variables, and so on.*". Moreover, as pointed out by Barros (2011) "*… these features could be relevant to our analysis because randomness is a main property of airport results*". Therefore, the present paper uses SFA to measure the efficiency of Peruvian airports. In order to put our paper into proper context, and to show the contribution of the article, Table 1 provides a summary of the papers that use SFA to measure efficiency in the airport sector.

In order to measure efficiency, it is necessary to define the technology of reference. To do this, in a parametric context, authors have to make three decisions: first, whether to consider more than one output; second, the functional form to be used in the empirical application; and finally, whether to use a homogenous or heterogeneous frontier, which depends on their assumption whether airports are homogeneous units or not.

With regard to the functional form chosen, the reviewed studies are divided into those that use a Cobb-Douglas function, 8 out of 30 (Pels et al., 2001; Assaf, 2009; Yang, 2010; Ha et al., 2013; Chen and Lai, 2019; Kaleab and Heshmati, 2021; Matulova and Rejentova, 2021; Present work), those that use a Translog function, 20 out of 308 (Martín-Cejas, 2002; Pels et al., 2003; Barros, 2008a; Barros, 2008b; Oum et al., 2008; Barros, 2009; Martín et al., 2009; Tovar and Martin-Cejas, 2009; Tovar and Martín-Cejas, 2010; Barros, 2011; Barros et al., 2011; Scotti et al., 2012; Kutlu and McCarthy, 2016; Barros, 2017; Fernández et al., 2018; Hidalgo-Gallego and Mateo-Mantecón, 2019; Martini et al., 2020; Ripoll-Zarraga and Raya, 2020; Karanki and Lim, 2021; Ripoll-Zarraga and Huderek-Glapska, 2021), and those that use both in order to test which functional form produces a better fit, 2 out of 30, (De la Torre, 2009; Assaf et al., 2012).

No matter whether a Cobb-Douglas or a Translog function is employed, the studies are divided between those that consider only one output and, therefore, choose a production function, 9 out of 32 (Pels et al., 2001; Pels et al., 2003; Assaf, 2009; Yang, 2010; Ha et al., 2013; Barros, 2017; Chen and Lai, 2019; Kaleab and Heshmati, 2021; Matulova and Rejentova, 2021), and those that take into account the multi-output nature of the airport industry. In this second group, authors could choose between a cost function, 14 out of 32 (Martín-Cejas, 2002; Barros, 2008a; Barros, 2008b; Oum et al., 2008; Barros, 2009; De la Torre, 2009; Martín et al., 2009; Marques and Barros, 2010; Barros, 2011; Barros et al., 2011; Assaf et al., 2012; Kutlu and McCarthy, 2016; Martini et al., 2020; Karanki and Lim, 2021), and a distance function, 9 out of 32, (Tovar & Martin-Cejas, 2009; Tovar and Martín-Cejas, 2010; Scotti et al., 2012; Fernández et al., 2018; Hidalgo-Gallego and Mateo-Mantecón, 2019; Ripoll-Zarraga and Raya, 2020; Ripoll-Zarraga and Huderek-Glapska, 2021; Ripoll-Zarraga, 2023; Present work). As Table 1 shows, the choice of a distance function has become increasingly popular since the first study employing it in 2009. This is, probably, due to the fact that the distance function has several advantages, which are particularly suitable for regulated industries, such as not having to make behavioural assumptions or not having to know input and output prices (Tovar and Martín-Cejas, 2009).

Regarding whether the airports studied are considered homogeneous or heterogeneous units, our literature review shows that 13 out of 32 used standard parametric models that did not allow for possible technological differences among airports; they assumed that all airports in the sample were homogeneous (Pels et al., 2001; Martín-Cejas, 2002; Pels et al., 2003; Barros, 2008a; De la Torre, 2009; Martín et al., 2009; Tovar & Martin-Cejas, 2009; Tovar and Martín-Cejas, 2010; Yang, 2010; Assaf et al., 2012; Ha et al., 2013; Matulova and Rejentova, 2021;

Table 1
Summary of parametric frontier airport efficiency studies.

Year	Authors	Methodology			Eficiency Measures	Data	Goal/Observations
		(1)	Model	Funtional Form			
2001	Pels et al.	YES	SPFM	CDF	TE	34 European airports (1995/1997)	Measures relative inefficiency. Doesn't explain the inefficiency
2002	Martín-Cejas	YES	DCFM	TF	CE	40 Spanish airports (1996–1997)	Analyses productive efficiency Possible inefficiencies are related to airport size.
2003	Pels et al.	YES	SPFM	TF	TE	34 European airports (1995/1997)	Examines whether size influences airports' efficiency Explains the inefficiency
2008	Barros(a)	YES	SCFM	TF	CE	10 Portuguese airports (1990–2000)	Analyses the rate of TC TC split into pure, non-neutral and scale-augmenting TC
	Barros(b)	NO	SCFM TRECFM	TF	CE	27 UK airports (2000–2005)	Estimates TE Different test (likelihood and chi-square) advocate using the heterogeneous frontier
	Oun et al.	NO	TRECFM	TF	CE	109 World airports (2001–2004)	Examines the effects of ownership on airports' CE Uses Bayesian approach
2009	Assaf	NO	MSPFM	CDF	TE	27 UK airports (2002–2007)	Compares the TE of small and large airports using a metafrontier
	Barros	NO	LCSCFM	TF	CE	27 UK airports (2000–2006)	Estimates TE The airports were segmented by the cost frontier into three classes
	De la Torre	YES	SCFM	CDF, TF	CE	12 Peruvian airports (2004–2008)	Estimates TE Productivity changes at airports were measured via a Malmquist index
	Martin et al.	YES	SCFM	TF	CE	37 Spanish airports (1991–1997)	Evaluates relative inefficiency Uses Bayesian methods and MCMC simulation
	Tovar & Martin-Cejas	YES	SIDFM	TF	TE	26 Spanish airports (1993–1999)	Estimates and explains airports technical efficiency
2010	Marques & Barros	NO	TRECFM	TF	CE	32 European airports (2001–2004)	Evaluates efficiency taking into account the endogenous managerial practices, ownership and regulatory control on the heterogeneous cost frontier. Suggests that homogenous frontier models should be abandoned
	Tovar & Martin-Cejas	YES	SIDFM	TF	TE	26 Spanish airports (1993–1999)	Evaluates relative inefficiency Productivity changes at airports were measured through a MI
	Yang	YES	SPFM	CDF	TE	12 airports Asia–Pacific (1998–2006)	Explains airports' efficiency.
2011	Barros	NO	LCSCFM	TF	CE	17 Angola & Mozambique airports (2000–2010)	Evaluates cost efficiency The airports were segmented by the cost frontier into three classes
	Barros et al.	NO	LCSCFM	TF	CE	16 Japanese airports (1987–2005)	Evaluates cost efficiency The airports were segmented by the cost frontier into two classes
2012	Assaf et al.	YES	DSCFM	CDF, TF	CE	27 UK airports (1998–2008)	Evaluates cost efficiency Uses Bayesian methods and explains airports' efficiency
	Scotti et al.	NO	SODFM	TF	TE	38 Italian airports (2005–2008)	How competition affects airports' technical efficiency
2013	Ha et al.	YES	SPFM	CDF	TE	11 Northeast Asian airports (1994–2011)	Examines the impact of airline market structure on airports' TE using a second-stage estimation
2016	Kutlu & McCarthy	NO	TFECFM	TF	CE	50 US airports (1996–2008)	Examines the effects of ownership on airports' CE Results change substantially if heterogeneity is not controlled
2017	Barros	NO	SPFM SPUMFM	TF	TE	30 Nigerian airports (2003–2014)	Unobserved managerial ability impact in TE is assessed
2018	Fernández et al.	NO	TFESIDFM	TF	TE	35 Spanish airports (2009–2016)	Evaluates the impact of tourism on airports' TE
2019	Chen & Lai	NO	DSPFM	CDF	TE	20 airports European and Asia-Pacific (2001–2013)	Evaluates the impact of ownership on airports' TE
	Hidalgo-Gallego & Mateo-Mantecón	NO	TFESIDFM	TF	TE	41 Spanish airports (2009–2014)	Examines the impact of airline market structure on airports' TE
2020	Martini et al.	NO	CSNSF	TF	CE	21 Italian airports (2010–2015)	Evaluates the impact of ownership on airports' TE Separates persistent and transitory inefficiency
	Ripoll-Zarraga & Raya	NO	TFESIDFM	TF	TE	48 Spanish airports (2009–2013)	Evaluates the impact of tourism on airports' TE
2021	Kaleab & Hesmati	NO	CSNSF	CDF	TE	13 Ethiopian airports (2002–2017)	Evaluates labour use efficiency Separates persistent and transitory inefficiency
	Karanki & Lim	NO	TRECFM	TF	CE	55 U.S. hub airports (2009–2019)	Examines the impact of airport use agreements on the CE
	Matulova & Rejentova	YES	SIDFM	CDF	TE	115 European airports 2018	Evaluates the impact of ownership on airports' TE
	Ripoll-Zarraga & Huderek	YES	SODFM	TF	TE	12 Polish airports (2009–2017)	Examines the impact of managers' theoretical knowledge and experience on airports' efficiency

(*continued on next page*)

Table 1 (*continued*)

Year	Authors	Methodology			Efficiency Measures	Data	Goal/Observations
		(1)	Model	Funtional Form			
2023	Ripoll-Zarraga	NO	TFESIDFM	TF	TE	48 Spanish airports (2009–2013)	Estimates the frontier following BC-95. Explain TE through regression models in a second stage.
	Present work	NO	LCSIDFM	CDF	TE	17 Peruvian airports (2004–2017)	Evaluates TE The airports were segmented by the input distance frontier into two classes

(1) Whether homogeneous technology is assumed.
Note: TE = Technical Efficiency; CE= Cost Efficiency; TC = Technical Change; CDF= Cobb-Douglas function; TF = Translog function; MI = Malmquist Index; DPFM = Deterministic Cost Frontier Model; SPFM = Stochastic Production Frontier Model; SCFM = Stochastic Cost Frontier Model; DSCFM = Dynamic Stochastic Cost Frontier Model; DSPFM = Dynamic Stochastic Production Frontier Model; SIDFM = Stochastic Input Distance Frontier Model; SODFM = Stochastic Output Distance Frontier Model; MSPFM = Metafrontier Stochastic Production Frontier Model; LCSCFM = Latent Class Stochastic Cost Frontier Model; LCSIDFM = Latent Class Stochastic input Distance Frontier Model; TRECFM = True Randon Effect Cost Frontier Model; TFEPFM = True Fixed Effect Production Frontier Model; TFESIDFM = True Fixed Effect Stochastic Input Distance Frontier Model; SPUMFM = Stochastic Production Unobserved Managerial Frontier Model; CSNSF = Closed Skew Normal Stochastic Frontier.
Source: own elaborated from several studies

Ripoll-Zarraga and Huderek-Glapska, 2021) while the other 19 took into account heterogeneity by either including exogenous variables in the frontier (Scotti et al., 2012) or by using more sophisticated stochastic models: Random Frontier Model (Barros, 2008b; Oum et al., 2008; Marques and Barros, 2010); True Fixed Effect Frontier Model (Kutlu and McCarthy, 2016; Fernández et al., 2018; Hidalgo-Gallego and Mateo-Mantecón, 2019; Ripoll-Zarraga and Raya, 2020; Karanki and Lim, 2021; Ripoll-Zarraga, 2023); Metafrontier Frontier Model (Assaf, 2009); Dynamic Stochastic Production Frontier Model (Chen and Lai, 2019); Closed Skew Normal Stochastic Frontier Model (Martini et al., 2020; Kaleab and Heshmati, 2021); Unobserved Managerial Frontier Model (Barros, 2017); Latent Class Frontier Model (Barros, 2009; Barros, 2011; Barros et al., 2011; Present work).

When it comes to the distribution by continent, Table 1 shows that the majority of studies, 16 out of 32, analysed airports located in Europe: eight in Spain (Martín-Cejas, 2002; Martín et al., 2009; Tovar and Martín-Cejas, 2009; Tovar and Martín-Cejas, 2010; Fernández et al., 2018; Hidalgo-Gallego and Mateo-Mantecón, 2019; Ripoll-Zarraga and Raya, 2020; Ripoll-Zarraga, 2023); four in the UK (Barros, 2008b, 2009; Assaf, 2009; Assaf et al., 2012); two in Italy (Scotti et al., 2012; Martini et al., 2020); one in Portugal (Barros, 2008a) and another in Poland (Ripoll-Zarraga and Huderek-Glapska, 2021). In addition, 4 out of 32 articles analysed airports located in the Americas: two in Peru (De la Torre, 2009; present work) and two in the USA (Kutlu and McCarthy, 2016; Karanki and Lim, 2021); another 4 out of 32 analysed airports located in Asia: one in Japan (Barros et al., 2011); two in Asia-Pacific (Yang, 2010; Chen and Lai, 2019) and one in Northeast Asia (Ha et al., 2013); other 3 out of 32 analysed airports located in Africa: one in Nigeria (Barros, 2017), one covering two countries: Angola and Mozambique (Barros, 2011) and another in Ethiopia (Kaleab and Heshmati, 2021); and there were none related to airports located in Oceania. Finally, we only found four articles that pooled airports on a continental basis (Pels et al., 2001, 2003; Marques and Barros, 2010; Matulova and Rejentova, 2021) and one article on a global basis (Oum et al., 2008).

Finally, as far as goals are concerned our review shows that 18 out of 32 attempt to identify factors influencing airport efficiency including, among others: a slot coordinated airport (Pels et al., 2003), time restrictions (Pels et al., 2003), ownership type (Oum et al., 2008; Scotti et al., 2012; Kutlu and McCarthy, 2016; Chen and Lai, 2019; Martini et al., 2020; Matulova and Rejentova, 2021; Ripoll-Zarraga and Huderek-Glapska, 2021), size (Assaf, 2009; Assaf et al., 2012), outsourcing (Tovar and Martín-Cejas, 2009), non-aeronautical activities (Tovar and Martín-Cejas, 2009), competition (Assaf et al., 2012; Scotti et al., 2012; Ha et al., 2013; Ripoll-Zarraga, 2023); regulation (Assaf et al., 2012; Ripoll-Zarraga, 2023); airline market structure (Ha et al., 2013; Hidalgo-Gallego and Mateo-Mantecón, 2019; Martini et al., 2020); managerial experience (Marques and Barros, 2010; Ripoll-Zarraga and Huderek-Glapska, 2021); airport use agreements (Karanki and Lim, 2021); labour use (Kaleab and Heshmati, 2021); tourism (Fernández et al., 2018; Ripoll-Zarraga and Raya, 2020) while the rest only measured airport efficiency.

3. Peruvian airport sector

The development of enhanced airport infrastructure is crucial in the Peruvian context. On the one hand, this is because land connectivity in Peru is limited and challenging due to the extremely rugged geography caused by the presence of the Andes Mountain Range, which runs longitudinally along the country. On the other hand, Peru has significant tourism potential, both domestically and internationally, since it is one of the world's most biodiverse countries with rich archaeological sites and renowned gastronomy. Consequently, the development of airport infrastructure is crucial. Thus, air transport infrastructure has become a key public policy issue.

3.1. *Privatization process*

Traditionally, air transport infrastructure in Latin America (LATAM) had been exclusively publicly owned and managed. Nevertheless, a series of reforms began in the 1990s due to the insufficient allocation of financial resources, the high dependence on the public budget, the excessive number of workers and the lack of technical criteria for making investments and recruiting qualified personnel. These reforms were linked to the introduction of private sector participation schemes[1] via the provision of airport services through public-private partnerships (PPP) arrangements.

From 1943 to 1992, the management of airport infrastructure and the provision of services at Peruvian airports were carried out by the national company Corporación Peruana de Aeropuertos y Aviación Comercial (CORPAC). In 1992, however, a process of airport reform was initiated with the enactment of the Decree-Law 25912, aimed at encouraging private investment. Decree-Law 25912 established that CORPAC would provide aeronautical services throughout the national airport network and would only run airport services at non-concessioned airports.

The main benefits sought with private participation in this sector are related to the improvement of the quality of airport services, the development of foreign trade, tourism and regional integration. Other

[1] Airport privatization could take different forms: share flotation, trade sale, concession, project finance privatization or management contract (Chen et al., 2017).

associated benefits were expected to be innovation and increased investment to improve the operational and commercial efficiency of airports. In addition, the promotion of direct cargo and passengers transport would lead to improvements in competitiveness. Thus, a series of modernization reforms was launched in the 2000s to encourage private investment and improve the quality and safety of airport operations.

The airport concession process in Peru has been carried out in three stages. The privatization process began in 2001 with the tendering of the country's main airport, the Jorge Chávez International Airport, to the Lima Airport Partners S.A. (LAP). Subsequently, in 2006, the first group of regional airports, comprising twelve airports in the north and centre of Peru, was concessioned to Aeropuertos del Perú S.A. (ADP), and in 2011, the second group of regional airports, comprising five airports in the south, was concessioned to Aeropuertos Andinos del Perú S.A. (AAP). The concession process for these regional airports was based on a PPP agreement, in which the government and the private operator share the construction and revenue risks (Aguirre et al., 2019). Finally, technical studies are currently underway to continue with the concession of the third group of regional airports, comprising eight airports.

3.2. Regulatory scheme

In Peru, airports offer both airport services and air navigation services; the latter are the exclusive responsibility of CORPAC. Air navigation services include aeronautical communications, air traffic control, meteorological services, en-route air navigation services and approach services. The tariffs for these services are adjusted annually for inflation and regulated by the Supervisory Agency for Investment in Public Use Transport Infrastructure (OSITRAN).

Airport services are managed by CORPAC or by private concessionaires under Public-Private Partnerships (PPP).[2] In the latter case, the regulation of airport services is included in the specific concession contracts, where clear obligations are established regarding investments in infrastructure and compliance with international standards of operational quality and safety, according to the guidelines established by the International Civil Aviation Organization (ICAO).

Although the airports under concession have similar regulatory criteria, there are specific differences in the initial tariff structure, the schedule for annual tariff adjustments and the complementary mechanisms for financing the required investments. On the other hand, the airports under direct administration of CORPAC depend exclusively on the state budget, which significantly limits its capacity to make important investments in airport infrastructure modernization and technology.

Airport tariff regulation in Peru is based on two main models: rate-of-return and price-cap regulation. The choice of the type of regulatory scheme is based on the investment needs, demand characteristics and economic and financial sustainability of the airports and have different implications in terms of incentives and risks for the operators.

In the case of regional airports, those managed by CORPAC as well as those concessioned to AdP and AAP, a cost of service regulation is applied, which aims to ensure that tariffs cover operating and investment costs and allow companies to earn a reasonable return on invested capital. The methodology used by OSITRAN to set tariffs is discounted cash flow, taking into account projected demand, operating costs, capital base and an opportunity cost of capital. However, Jorge Chávez International Airport is the only Peruvian airport that is subject to a maximum tariff system. This model sets a maximum limit on the tariffs that the concessionaire can charge, which encourages operational efficiency and allows the operator to retain the gains from efficiency improvements during the regulatory period. Tariffs are periodically adjusted using the "RPI-X″ mechanism, where RPI is the consumer price index and X is the productivity factor estimated by OSITRAN.

Therefore, the main difference between these models lies in the incentives and risk transfer. While the cost-of-service model guarantees cost recovery and reasonable profitability, the price-cap model provides incentives for operators to improve efficiency and reduce costs, since they can retain the profits derived from such improvements. However, the latter also transfers the risk associated with fluctuations in input costs and demand to the operator.

Cost of service regulation is an appropriate scheme in the case of regional airports since they still require investment in infrastructure and equipment for their proper operation. According to OSITRAN's performance reports (2024), AdP invested around USD 24 million in modernization and improvement of airport infrastructure during 2023, while AAP allocated approximately USD 9.4 million to the rehabilitation and expansion of the airports under its concession. On the other hand, CORPAC executed investments of approximately USD 9.8 million in 2023, representing only 37.2 % of the initially projected budget, which reflects clear budgetary and execution limitations in the provision of its services. This restriction could influence the technical efficiency observed, generating potential differences with respect to airports managed through PPPs (Aguirre et al., 2019).

From a regulatory perspective, these potential differences justify the need to explicitly account for unobserved heterogeneity in the comparative assessment of regional airport efficiency if the bodies responsible for formulating public policy, such as the MTC, the Ministry of Economy and Finance (MEF), OSITRAN and ProInversión, were to use measures of airport operators' performance for regulatory or normative purposes. This would encourage operational improvements and avoid one-size-fits-all regulatory schemes.

The literature on yardstick competition and incentive regulation shows that using homogeneous frontiers can lead to biased efficiency rankings and distorted regulatory incentives (Shleifer, 1985; Burns et al., 2005). In environments characterized by high operational diversity, heterogeneity-adjusted benchmarking mechanisms allow for a more accurate identification of performance differences attributable to managerial efficiency rather than structural or market conditions, strengthening the credibility and effectiveness of regulation (Agrell and Bogetoft, 2016).

4. Methodology

The aim of this paper is to assess and compare the efficiency of Peruvian regional airports in order to evaluate whether the reform process has improved the technical efficiency of regional airports. The second objective is to identify possible technological differences among these airports.

It should be noted that when evaluating and comparing efficiencies, one issue of great importance is the treatment of heterogeneity; this is because if such heterogeneity exists, and it is not explicitly picked up in the model, the estimated coefficients of the variables included in the model will be biased. This issue becomes relevant in our case because of the potential differences due to the airports belonging to different geographical zones, having different traffic, ownership, regulatory schemes, and so on.

The traditional SFA models for panel data do not consider the unobserved heterogeneity. Therefore, the efficiency measurements could be erroneous, and unobserved factors might be inappropriately understood as inefficiency. Broadly speaking, two types of models can be used to mitigate this problem in a parametric approach. The first type of models assumes that all firms share the same technology, and the unobserved heterogeneity is modelled as an individual effect, and the second type of models relax the assumption that all firms share the same technology (Chang and Tovar, 2017). This is the approach taken in this paper to account for possible technological differences among airports.

Therefore, we will assess and compare the efficiency of Peruvian

[2] A review of Peru's infrastructure airport concession process is beyond the scope of this paper, but an overview can be found in Aguirre et al. (2019).

regional airports through the following LCSFM:

$$y_{it} = f(\beta_j, x_{it})^* \exp\left(\epsilon_{it}|_j\right); \quad \epsilon_{it}|_j = v_{it}|_j - u_{it}|_j \tag{1}$$

where $i = 1, \ldots, N$ represents airport; $t = 1, \ldots, T_i$ designates time, and $j = 1, \ldots, J$ denotes the classes, and vertical bars symbolise that there is a different model for each class j.

On the basis of the information gathered, it is possible to make different specifications of the model depending on whether a production function or a distance function is modelled. We chose the distance function because it has the advantage of not requiring input and output prices, but also, and more importantly in our case, because it describes multi-input/multi-output production technology without making behavioural assumptions (e.g. cost minimisation or profit maximisation).

Moreover, in order to estimate a distance function, it is necessary to choose the model orientation. The latter depends on which variables, inputs or outputs, the firms have more control over. In particular, given the characteristics of regional airports, which have captive demand from their area of influence and natural monopoly characteristics, an input orientation was chosen.

Finally, a functional form should be chosen. The flexible translog and Cobb-Douglas functional forms are the most commonly used (see section 2).[3] Our model of LCSFM is the following Cobb-Douglas input distance function, which includes time effects to control for factors that may affect all airports in the same way but vary over time:

$$-ln(x_{Mit}) = \alpha_0|_j + \sum_{r=1}^{N} \alpha_r|_j{}^* ln\, y_{rit} + \sum_{s=1}^{M-1} \beta_s|_j{}^* ln\, x_{sit} + \mathrm{t} + \mathrm{t}^2 +$$

$$\sum_{r=1}^{N} \theta_r|_j{}^* \mathrm{t}^* ln\, y_{rit} + \sum_{s=1}^{M-1} \gamma_s|_j{}^* \mathrm{t}^* ln\, x_{sit} + v_{it} + u_{it} \tag{2}$$

Where N = outputs and M = inputs.

The class probabilities can be parameterized by a multi-nomial logit model:

$$P_{ij} = \frac{exp(\delta_j AdP_i)}{\sum_{j=1}^{J} exp(\delta_j AdP_i)} \tag{3}$$

where AdP_i is a vector of airport-specific but time-invariant variable.

This variable, called separating, is an individual characteristic that sharpens the prior probabilities and can be included to identify any regularity in the classification of the sample through the estimated coefficients of the latent class probability functions $\widehat{\delta}_j$ (Greene, 2008). A positive (negative) sign of the coefficient δ indicates that when AdP is 1, the probability that a terminal belongs to Class 1 increases (decreases).

The estimated parameters can be used to compute posterior class membership probabilities using the following expression:

$$P(j, t|i) = \frac{P_{ij} LF_{ijt}}{\sum_{j=1}^{J} P_{ij} LF_{ijt}} \tag{4}$$

These posterior probabilities of membership can then be used to allocate each firm to a particular class, e.g., each firm is assigned to the class with the higher posterior probability. Finally, due to the problems identified by Greene (2005) regarding the use of the likelihood ratio to select the number of classes, the Akaike Information Criterion (AIC) or the Schwarz Bayesian Information Criterion (SBIC) are generally used as alternative methods (Chang and Tovar, 2017).

5. Data

This study analyses a sample of seventeen regional airports located throughout the country (see Fig. 1 below): Cusco, Cajamarca, Chachapoyas, Anta Huaraz, Iquitos, Pucallpa, Talara, Tarapoto, Trujillo, Tumbes, Pisco, Chiclayo, Piura, Arequipa, Juliaca, Puerto Maldonado and Tacna, which account for 82.4 % of regional airport traffic in Peru. 12 of the 17 airports are operated by ADP, 4 by AAP and 1 by CORPAC. The analysis period covers the years 2004 and 2017.

Table 2 provides general information on some important characteristics of the airports analysed, such as the geographical location, the company providing operation and maintenance services, the year in which the airport was transferred to private management, the altitude, whether the traffic is mainly tourist and the size of the runway.

With regard to the variables required to estimate the model, they must allow the airport's production process to be represented. In this sense, input and output variables are required to represent the factors of production as well as the services provided by the airport. Our choice of output and input variables, presented below, follows the general consensus found in the literature[4] and the available data.

The multi-output nature of airport services has been recognised in the literature (Yoshida and Fujimoto, 2004; Tovar and Martín-Cejas, 2010). Therefore, in terms of outputs, it is necessary to characterise not only the services provided to the intermediate users (airlines), but also those provided to the final users (passengers and logistics operators). For this purpose, information was collected on the number of operations performed by airlines (landings and take-offs), which represent the output of airside operations, and the number of passengers and tons of cargo, which correspond to the output of airport landside operations. As regards inputs, information was obtained corresponding to variables expressed in monetary terms, which were deflated in order to express them in real terms. These variables are operating expenses comprising all expenses minus capital-related costs and capital, approximated by the stock of net fixed assets, i.e. the book value of tangible long-term assets (buildings, constructions, and machinery and equipment) net of accumulated depreciation. Both variables are expressed in Miles de Soles (MS), in constant values (year 2004 = 100).

On the other hand, the LCSFM methodology allows us to include certain observable variables, called separating variables, which contribute to the identification of the classes. Among the available separating variables, the best model was the one that included the AdP variable, a qualitative variable that takes the value 1 if the airport is managed by the AdP concessionaire and zero in otherwise.

The descriptive statistics of the variables used in the estimated models are presented in Table 3. These data were obtained from the annual reports of CORPAC, AAP, ADP and OSITRAN and from their respective websites.

As shown in Table 3, the variable cargo is highly dispersed. Moreover, several airports do not handle any cargo (minimum value of zero) or handle very small quantities. For the latter reasons, we decided not to include cargo as a separate output and to consider only two outputs: passengers and operations. However, in order to analyse whether the cargo could have an impact on the efficiency results, we also estimated a model where we included the workload unit (WLU) which integrates passengers and cargo, instead of passengers. The WLU assumes that one passenger corresponds to 100 kg, and it has been used in several airport efficiency studies (e.g. Martín et al., 2009; Hidalgo-Gallego and Mateo-Mantecon, 2019). The estimated models are summarised in Table 4, which also indicates the respective input and output variables,

[3] Although the translog function should be chosen as the first option in order to mitigate as much as possible the implications of assuming a particular functional form, in the presence of convergence problems as in our case, the choice of the Cobb-Douglas function is the appropriate option.

[4] The selected variables have been widely used in previous airport efficiency studies (see the reviews by Tovar and Martín-Cejas (2009) and Liebert and Niemeier (2013), to name but two.

Fig. 1. Peruvian airports analysed. Location and privatization status in 2017.
Source: Own elaboration

as well as the time related variables included in each model.

6. Results

Table 5 shows the best latent stochastic frontier models obtained from the available information. All models are Cobb-Douglas input distance functions with two classes and AdP as the separator variable.[5]

[5] The empirical results with three or four classes did not converge under maximum likelihood estimation, and the inclusion of other separator variables was not significant.

Table 2
Main characteristics of the Peruvian airports analysed (2004–2017).

Airport	Located in	Firm	Private since	Altitude (feets)	Turistic	Runway size (m^2)
Cusco	Mountain	CORPAC	–	10,860	Yes	3 520 x 150
Cajamarca	Mountain	ADP	2006	8,787	No	2 500 x 45
Chachapoyas	Jungle	ADP	2006	8,333	No	1 980 x 30
Anta Huaraz	Mountain	ADP	2006	9,097	No	3 050 x 30
Iquitos	Jungle	ADP	2006	306	Yes	2 500 x 45
Pucallpa	Jungle	ADP	2006	2,000	No	2 800 x 60
Talara	Coast	ADP	2006	31	No	2 500 x 45
Tarapoto	Jungle	ADP	2006	869	Yes	2 600 x 45
Trujillo	Coast	ADP	2006	128	Yes	3 000 x 45
Tumbes	Coast	ADP	2006	115	Yes	2 500 x 45
Pisco	Coast	ADP	2008	40	No	3 020 x 45
Chiclayo	Coast	ADP	2008	97	No	2 500 x 45
Piura	Coast	ADP	2008	101	Yes	2 500 x 45
Arequipa	Mountain	AAP	2011	8,400	Yes	2 980 x 45
Juliaca	Mountain	AAP	2011	12,552	Yes	4 200 x 45
Pto. Maldonado	Jungle	AAP	2011	659	Yes	3 500 x 45
Tacna	Coast	AAP	2011	1,538	No	2 500 x 45

Source: Own elaboration

Table 3
Descriptive statistics.

Variable		Observation	Mean	Std. Dev.	Min	Max
Outputs	Passenger (unit)	238	381,905	517,836	35.0	3,389,166
	Cargo (kg)	238	1,546,417	2,786,703	0	16,000,000
	WLU (/000)	238	39,680	52,445	3.5	339,832
	Operation (unit)	238	7,785	9210	4.0	53,252
Inputs	Capital (MS, year 2004 = 100)	238	16,700,000	12,700,000	3,278,741	58,600,000
	Operating expenses (MS, year 2004 = 100)	238	2,187,205	1,740,546	104,849	11,300,000
Separating variable	AdP (1/0)	238	0.54	0.50	0	1

Source: Own elaboration

Table 4
Variables in the estimated models.

	Outputs			Inputs		Time			
	Passenger	WLU	Operation	Operating expenses	Capital	t	t^2	t x outputs	t x inputs
Model 1	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model 2	No	yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model 3	No	yes	Yes	Yes	Yes	Yes	Yes	No	No

Source: Own elaboration

Moreover, they have the consideration of two input variables in common: Operating Expenses and Capital, and one output: operation (that of the downstream user –airlines-); however, they differ in the second output included to represent the final user output (passenger for model 1 and WLU for models 2 and 3) and in the way the time trend is included in the distance function (only time and time squared for model 3 or also all cross terms for models 1 and 2).

Table 5 shows that the three estimated models have very similar significant coefficients for the first-order parameters, the cross terms, the separator variable and also for sigma and lambda, the coefficients that justify the estimation of a stochastic frontier model. However, according to the information criteria, the best is model 2.

The estimated first-order parameters for model 2, in Table 5, are the input-output elasticities. They have the correct sign and are statistically significant at the 1 % level. Furthermore, the variance parameters, sigma and lambda, are statistically significant at the usual levels, and the estimated values of the lambda parameters are 1.38 and 2.53 for Class 1 and Class 2 respectively, indicating that the effects related to inefficiency are more significant than those related to statistical noise for regional airports. In addition, the separator variable was positive and significant, showing that airports operated by the ADP concessionaire are more likely to be in Class 1.

Regarding the output elasticities of model 2, they differ between classes, with Class 1 showing higher elasticities for both output variables: WLU and operations than Class 2. The elasticities also differ for inputs. Class 1 has a higher elasticity for capital input, while Class 2 has a higher elasticity for operating expenses. The scale elasticities can be obtained as the inverse of the negative sum of the first order output coefficients. These scale elasticities are 0.3993 and 0.2583 for Class 1 and 2 respectively, showing the existence of increasing returns to scale, which are more pronounced for Class 2.

The results also indicate that both classes have experienced technological progress, especially airports in Class 2, as shown by the first order parameters of the time variable (0.0932 and 0.1410 for Class 1 and Class 2, respectively), which were statistically significant. However, this technical progress decreases over time, as shown by the negative and significant coefficient of the quadratic time terms (−0.0064 and −0.0116 for Class 1 and Class 2, respectively).

Moreover, our estimation shows an operating expenses biased technical change, as this variable increases the productivity of airports belonging to both classes. The cross derivatives between input and time show that the greater the operating expenses (or less capital), the higher

Table 5
Estimated models.

Variables	Model 1		Model 2		Model 3	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
Constant	0.3045***	0.2442***	0.3204***	0.2432***	0.4053***	0.2089***
Passenger	−0.1661***	−0.0765***				
WLU			−0.1730***	−0.0785***	−0.1880***	−0.0870***
Operation	−0.2315***	−0.1769***	−0.2263***	−0.1753***	−0.2126***	−0.1413***
Operating expenses	0.7938***	0.8625***	0.7955***	0.8711***	0.7885***	0.7930***
Capital	0.2054***	0.1367***	0.2040***	0.1355***	0.2070***	0.2115***
T	0.0929*	0.1389***	0.0932*	0.1410***	0.1231***	0.1326***
t x t	−0.0063*	−0.0114***	−0.0064**	−0.0116***	−0.0080***	−0.0110***
t x Passenger	−0.0078	−0.001				
t x WLU			−0.0059	−0.0009		
t x operation	−0.0009	−0.0063	−0.0020	−0.0067		
t x operating expenses	0.0139***	0.0653***	0.0137***	0.0660***		
t x capital	−0.027*	−0.0227***	−0.0257***	−0.0227***		
Sigma	0.3509***	0.4283***	0.3619***	0.4275***	0.4377***	0.4164***
Lambda	1.1949*	2.5241**	1.3780*	2.5323**	2.2162***	2.1063***
Estimated prior probabilities for class membership						
Constant	−1.2537		−1.2538		−1.2649	
ADP	2.5024**		2.4851**		3.1018**	
Prob *Class*	0.52302***	0.47698**	0.52068***	0.47932***	0.59949***	0.40051**

Source: Own elaboration

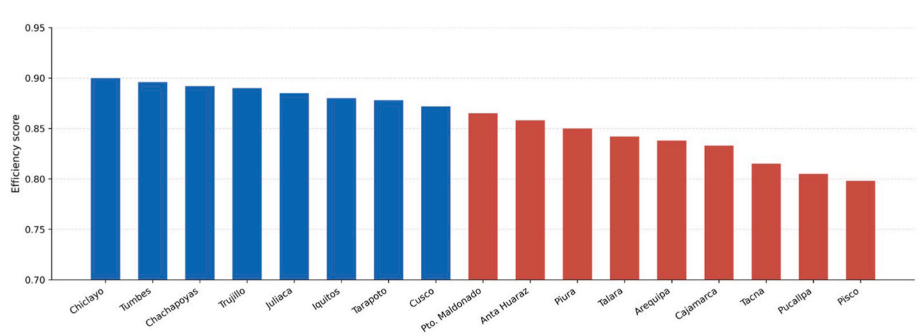

Fig. 2. Technical Efficiency, by airport, 2004–2017.
Source: Own elaboration

the technological progress. Therefore, technological change has increased the marginal productivity of operating expenses more than the marginal productivity of capital in both classes. This non-neutral technical change biased towards operating expenses rather than capital, indicate that the marginal productivity of factor including in this variable (personnel, management, maintenance and support services) has increased as a result of technological improvements.

Finally, Table 5 shows that the estimated prior probabilities in the data averages are statistically significant at 1 % and the probability of belonging to each class is 52.06 % and 47.93 % for Class 1 and Class 2 respectively.

Fig. 2 shows the ranking of the efficiency levels of the class using the posterior probabilities of belonging to each class. As can be seen, the average technical efficiency of all airports in Class 1 is higher than that of airports in Class 2.

Fig. 3 shows the evolution of the average technical efficiency of each class. Again, Class 1 airports show higher levels of efficiency throughout the period of analysis between 2004 and 2017.

Table 6 presents the main characteristics (physical and technical variables) of the airports belonging to each class.

The averages of the Technical Efficiency (TE) index are calculated using the posterior probabilities as weights, considering the two distance functions as a frontier (see equation (4)).

$$TE_i = \sum_{j=1}^{J} P(j|i) * TE_{i|j} \tag{4}$$

Class 1 airports have a higher average technical efficiency (TE) than Class 2 airports. On average, Class 1 and Class 2 could have reduced their inputs by 11.1 % and 16.6 % respectively while producing the same amount of output, given their technological frontier. On the other hand, Class 1 includes mainly larger airports with higher passenger numbers, higher WLU and higher share of capital and operating expenses compared to Class 2 airports, while Class 1 has a lower share of Operations (explained by the operation of larger aircrafts).

The traffic at Class 1 airports is mainly tourist traffic compared to Class 2 airports. In terms of location, Class 1 airports are mostly located in the mountains and jungle, while Class 2 airports are mostly located on the coast. Finally, with regard to the type of management, Class 1 has a higher number of airports operated by AdP.

In summary, the results indicate that an input-oriented Cobb-Douglas with two latent classes and a separator variable (AdP) adequately captures technological heterogeneity. Specifically, out of the 17 airports studied, eight airports were classified in Class 1 and nine in Class 2. Moreover, and over the whole period, the airports classified in Class 1 show a higher level of technical efficiency than those classified in Class 2 (see Fig. 2 above). Similarly, management by AdP significantly increases the probability of an airport being classified in Class 1. In addition, there are clear differences between the two classes in terms of operational size and tourism orientation. Class 1 airports tend to be larger and more focused on inbound tourism, while Class 2 airports tend to be smaller and less focused on tourism. Finally, both classes show increasing returns to scale, which are more pronounced for Class 2. This last result could be explained by regional airports having natural monopoly characteristics.

Table 6
Characteristics of airports analysed, by class (averages values).

Variable	Class 1	Class 2
Technical efficiency	88.9 %	83.4 %
Passenger (unit)	497,446	279,202
WLU (/000)	51,887	28,830
Operations (unit)	7,452	8,081
Capital (MS, 2004 = 100)	15,700,000	17,500,000
Labour&Outsourcing (MS, 2004 = 100)	2,408,919	1,990,126
Turistic (1 = yes,0 = no)	0.75	0.33
Receptive tourism (unit)	222,125.80	90,813.51
Coast (1 = yes 0 = no)	0.4	0.6
Mountain (1 = yes 0 = no)	0.3	0.2
Jungle (1 = yes 0 = no)	0.4	0.2
AdP (1 = yes 0 = no)	0.6	0.5
Managment (1 = private 0 = public)	0.6	0.7

Source: Own elaboration

7. Conclusions and policy implications

In 1992, Peru introduced legislative reforms to promote private sector access to airport infrastructure, implemented in the case of regional airports through a PPP mechanism. In this paper we have addressed the impact of these changes in the regulatory environment on the efficiency of 17 Peruvian regional airports over the period 2004–2017.

The present article uses a latent class stochastic frontier model to take into account the unobserved heterogeneity of Peruvian regional airports when analysing their technical efficiency evolution. To the best of the author's knowledge, this is the first time that a multi-output stochastic distance function has been employed in a latent class context to analyse the technical efficiency of airports, addressing a very important area in the empirical literature related to efficiency issues.

The results shows that regional airports operate with two different technologies, with different intensities in terms of their productive factors and outputs and with increasing return to scale. Moreover, regional airports have shown sustained technological progress over time, suggesting that public-private partnerships (PPPs) in Peru have facilitated technology adoption and improved airport operational efficiency. It is therefore recommended that the concession processes for the third group of regional airports be accelerated.

The approach used in this paper, would allow improvements in the design and application of incentive-based regulatory mechanisms, such as price cap regulation, yardstick competition or regulatory

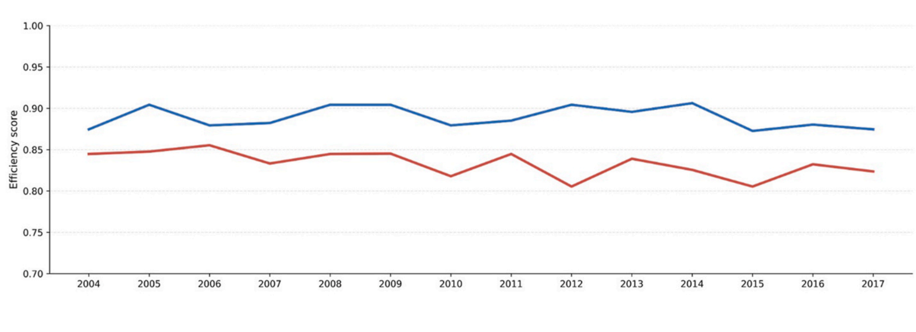

Fig. 3. Technical Efficiency, by class, 2004–2017.
Source: Own elaboration

benchmarking, all of which are available in the OSITRAN regulatory framework. Heterogeneity among Peruvian regional airports was revealed by our results. It is therefore recommended that regulators develop specific methodological frameworks that integrate such heterogeneity into their reference models, adjusting performance targets and tariff structures according to the actual operating conditions of each terminal.

On the other hand, it is recommended to continue with the system of airport concessions through PPPs by groups and to simplify the administrative procedures for the implementation of investments in airport infrastructure, both in concessioned airports and those under state management. Reducing project implementation times is key to meeting the growing demand for air connectivity, filling infrastructure gaps and improving regional competitiveness. These recommendations could be useful for policy makers, regulators and airport operators to consolidate an efficient regional airport system that is technologically adaptive and aligned with territorial development objectives.

Finally, the limitations of this study should be acknowledged. Firstly, due to the size of our panel data, our model assumes a modified Cobb-Douglas function and technological heterogeneity to be stable across the entire period within each class. Secondly, the available dataset does not include some regional airports that are still publicly owned and managed by CORPAC.

The future research agenda should be oriented towards evaluating changes in the productivity of regional airports, as well as incorporating a longer time perspective to analyse structural changes in technical efficiency and the factors that explain them. It is also proposed to extend the data set to include the twelve Peruvian regional airports that are still public and managed by CORPAC, in order to know their previous technical efficiency levels, and to be able to assess the impact on their efficiency levels if they were under private management. Similarly, it would be interesting to check whether our results might be affected by using a more flexible functional form (translog) and/or a dynamic latent class model to account for potential structural breaks or evolving heterogeneity patterns over time, when longer panel data is available. Finally, future research could include service quality and environmental sustainability indicators to enrich the overall evaluation of airport performance in the Peruvian context.

CRediT authorship contribution statement

Victor Chang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Beatriz Tovar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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