

THE IMPACT OF LOGISTICS AND INTERMODALITY ON AIRPORT EFFICIENCY

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Abstract

The operational performance of an airport is determined by the efficient management of passenger and cargo flows. This paper aims to analyse the impact of various logistics factors on the efficiency of major airports in Europe.

Using Data Envelopment Analysis (DEA), a comparative analysis has been estimated for the 21 largest European airports over the 2009-2014 period. At a second stage, this research analysed the effects that the *Logistics* and *Intermodality* have on airport efficiency.

The impact of logistics on overall airport efficiency is estimated at 0.15% for every 1% increase in Logistic Performance (LPI), *ceteris paribus*. The results show that airports that have a direct link to a High-Speed Rail (HSR) network were, on average, 23 per cent more efficient over the period. Moreover, the higher the percentage of Gates with fingers-bridges, the higher the levels of overall technical efficiency, pure technical efficiency, and scale efficiency.

Keywords: airports; efficiency; logistics; Intermodal; Europe; DEA;

Introduction

As the global economy is becoming more and more connected, so must the transportation, intermodality and the logistics systems. Thus, the transport industry is an increasingly contributing factor to the economy. According to the statistical office of the European Union (Eurostat, 2016), the contributions of transport – in gross value added- to the EU (28 countries) economy is estimated in €664bn (9% of total) employing around 11 million people.

Air transportation is a strategically important sector that makes a vital contribution to the EU's overall economy (EU Commission, 2018). The aviation market was gradually liberalised through three successive packages of measures adopted at EU level. Since 2004 the European airspace is subject to joint management (Eurocontrol 2016). Thus, in 2016, 10.2 million flights flew over European airspace, with an average of 27,844 daily flights which implies a somewhat complex air traffic control management.

45 The connectivity of an airport is defined as how “central” this airport is on those networks.
46 Main European airports aspire to become leading players in the global trade system. In the
47 Intermodal system, hubs are one of the critical elements that function as an interchanging of
48 passengers and goods between different modes (Van Dam et al. 2007).

49 The Single European Sky has caused a significant increase in the number of intracommunity
50 domestic routes (874 in 1992, 3,522 in 2015). Globally EU's trade with the rest of the world
51 represents 25% of all global air traffic (LEAHY 2015). According to the Airport Industry
52 Connectivity Report (2017), 5 EU airports rank among the 10 top global hubs in 2016.
53 Furthermore, regarding cargo traffic, Frankfurt continues to be the airport offering the best hub
54 connectivity in the world.

55 *Logistics is the process of planning, implementing and controlling procedures for efficient and*
56 *effective transportation and storage of goods, services, and related information from point of*
57 *origin to point of consumption* (Li, 2014). The expansion of traditional infrastructures such as
58 highways, terminals, and airports was essential for the development of modern logistics (Hesse
59 and Rodrigue, 2004). However, the complexity of international logistics systems has risen in
60 recent years, as a result of the massive developments in information and communication
61 technologies. An example of this is the hub and spoke system. Today, international
62 transportation is organized in complex networks formed by hubs and spokes.

63 In an increasingly competitive environment, it is therefore essential to find the critical
64 determinants of Air transport efficiency. There is no doubt that logistic and intermodality are
65 essential components of transportation development. Nevertheless, there have been few studies
66 on the impact of this phenomenon on transport efficiency (Lai et al., 2004, Min & Jong Joo,
67 2006, Fugate et al., 2010, Coto-Millán et al., 2015). Given these shortcomings, this paper seeks
68 to contribute to the already-rich debate on this topic by evaluating the impact of logistics and
69 intermodality on the efficiency of the large European airports. With this goal in mind, a sample
70 of data from 2009 to 2014 corresponding to 21 major European hubs has been studied.

71 We seek to contribute to the studies on airport efficiency in two respects. First, we present
72 evidence of a positive relationship between the national logistics system and the efficiency in
73 airports within 14 countries of the European Union. Second, we highlight the importance of
74 intermodality to achieve airport efficiency.

75 This research applies the double bootstrap method (Simar and Wilson, 2007) to investigate how
76 the external environment affect the efficiency levels. In the first stage, efficiency scores were
77 estimated for European airports (2009-2014 period). Next, the efficiency rated were regressed
78 on some relevant exogenous variables (the logistics system quality and the airport
79 intermodality) not included in the DEA analysis.

80 The rest of the document is structured as follows: The second section reviews the literature on
81 the most common topics investigated in airports. In the third section, we propose a theoretical
82 model. The fourth section describes the data used in the study and the main results. Finally,
83 section five sets out the main conclusions of the study.

84

85 **Literature review**

86 During the past two decades, there has been a great deal of research on airport efficiency. Gillen
87 & Lall (1997) pioneered the use of Data Envelopment Analysis techniques to study efficiency
88 in the airport sector. Using an output-oriented specification, the authors evaluated the efficiency
89 of 21 USA airports over the 1989-1992 period and found that size positively affects efficiency.
90 On the same vein Martín & Román, (2001) used a DEA approach to evaluate the efficiency of
91 37 Spanish airports. Based on 1997 data, the authors found a group of airports whose
92 performance was clearly poor, and therefore extracted some policy recommendations.

93 The question of whether size matters regarding efficiency or not has also been addressed by
94 Sarkis (2000). Using data envelopment analysis, the author evaluates the operational
95 capabilities of forty-four U.S. airports. Results suggest that operation managers should assess
96 and benchmark their performances with airports with similar characteristics. Most later research
97 found a positive relationship between size and efficiency (Pels et al., 2001, Tapiador et al.,
98 2008, Pestana et al., 2008, Perelman and Serebrisky, 2010). The exceptions are the work of
99 Abbot et al. (2002), who estimate the productivity of 12 Australian airports. Using data
100 envelopment analysis and a Malmquist total factor productivity index, the authors found no
101 relationship between the size and efficiency of airports.

102 Based on the available research, there is no consensus on the role of cargo in airport
103 performance. Coto-Millán et al. (2016) found a positive impact of the proportion of cargo traffic
104 in total traffic on the technical and scale efficiency of the Spanish airport infrastructure. The
105 authors argued that handling cargo is capital intensive and therefore more productive than
106 handling passengers are. Oum, Adler, & Yu, (2006) found a weak positive relationship between
107 the proportion of cargo traffic and variable factor productivity (VFP). On the contrary, Tovar
108 & Martín-Cejas, (2009) found an adverse effect on efficiency when the proportion of cargo that
109 circulates through terminals increases.

110 Most studies have defined airports as a multi-product business. Gillen & Lall (1997) argued
111 that airports offer two different classes of services: terminal services and movements. Martín
112 & Román, (2001) measured output using three variables: number of passengers, air traffic
113 movements, and the number of tonnes of cargo. Further work have provided an overview of the
114 input and output variables used in airport efficiency studies (Pels et al., 2001, Adler &
115 Berechman, 2001, Abrate & Erbetta, 2010, Tovar & Martín-Cejas, 2010, Liebert & Niemeier,
116 2013). Some typical outputs include: number of passengers, work load units, cargo tonnes,
117 aircraft movements, operational revenues, aeronautical revenues, and non-aeronautical
118 revenues. Common inputs include proxies of labor and capital, number of employees, number
119 of gates, number of check-in desks, surface area, operating costs, Non-operating costs, number
120 of runways, number of baggage collection belts and number of public parking places.

121 There has been some interest in the efficiency of the large European airports. Using different
122 partial ratios, Doganis et al. (1995) compared the relative performance of a group of European
123 airports with the average performance of 25 airports in the sample. Adler & Berechman (2001)
124 used DEA to analyse the quality and performance of 25 European airports from the airlines'
125 viewpoint. Pels et al. (2001) estimated the efficiency of 34 European airports using a stochastic
126 production frontier model and then compared it with technical efficiency scores derived from a
127 DEA analysis. The author finds a positive relationship between size and efficiency.

128 There have been other topics of interest in the study of European airports performance. Using
129 a sample of 57 European airports, Malighetti et al. (2009) studied the relationship between
130 airport efficiency and two factors: airport's centrality in the EU network and the intensity of
131 competition from alternative airports in the same catchment area. Authors find a positive
132 correlation between efficiency and centrality in the European system.

133 Randrianarisoa et al. (2015) analysed the effect of corruption on the efficiency of 47 European
134 airports for the period 2003-2009. Using a combination of multilateral index number methods
135 and robust cluster random effects models, the authors found substantial evidence that corruption
136 impacts negatively on the airport levels of efficiency.

137 Despite a significant amount of literature on airport efficiency, to the best knowledge of the
138 authors, there have been no studies regarding the extent to which logistics and intermodality
139 affect airport efficiency. This study is, according to our understanding, therefore the first to
140 analyse this effect.

141

142 **Methodology and data used**

143 **DEA Methodology**

144 Farrell (1957) suggested a deterministic method of measuring the technical efficiency of a firm
145 in an industry by estimating a frontier production function. Based on Farrell's work (Farrell
146 1957), Charnes, Cooper, & Rhodes, (1978) shape the deterministic non-parametric
147 methodological technique of Data Envelopment Analysis (DEA) to measure the relative
148 performance of a set of similar organisational units (DMUs) which, in this paper, correspond
149 to airports. In the regional airport context, Merkert et al. (2012) have shown that DEA models
150 are appropriate and useful for performance measurement with multiple inputs and outputs.

151 DEA methodology can be used to derive both technical and scale efficiency, and to determine
152 the nature of returns to scale. Furthermore, it can be used for measuring the relative performance
153 of organisational units where there is a presence of multiple inputs and outputs. A firm is
154 technically inefficient if production occurs within this production set. The inefficiency of a
155 DMU is measured by the distance from the point representing its observed input and output
156 values to the production frontier. A description of the DEA methodology is explained in Mantri
157 (2008).

158 DEA can be output or input oriented. On the one hand, a model is input-oriented when the
159 measure of efficiency is the distance between observed and minimum possible input for given
160 outputs, and on the other side, it is output-oriented when trying to determine the maximum
161 possible outputs with given levels of inputs.

162 Thus, for the j th airport out of n airports, the input-oriented technical efficiency under constant
163 return to scale (CRS) is obtained by solving the following linear programming problem:

$$\min_{\theta_j^{CRS}, \lambda} \theta_j^{CRS} \text{ subject to : } \theta X_j \geq X\lambda; Y_j \leq Y\lambda; \lambda \geq 0 \quad (1)$$

164 Where X and Y are the input and output vectors, respectively, $\phi_j^{CVS} = 1/\theta_j^{CVS}$ is the technical
165 efficiency (TE) of airport j under CRS and λ is an $n \times 1$ vector of weights. The non-negative
166 weights λ measures the contribution of the efficient airports selected to define a point of
167 reference for the inefficient j th airport. In general, $0 \leq \phi_j^{CRS} \leq 1$, where $\phi_j^{CRS} = 1$ if the airport
168 is producing on the production frontier and hence, technically efficient. When $\phi_j^{CRS} < 1$, the
169 airport is technically inefficient. In the case of variable returns to scale, one can find technical
170 efficiency ϕ_j^{VRS} by adding the convexity constraint $\sum_{j=1}^n \lambda_j = 1$ to (1) (Banker et al., 1984).

171 Because the distances are the technical efficiency scores from CRS-DEA and VRS-DEA
172 models, scale efficiency (SE) can be easily obtained by the ratio of technical efficiency scores
173 of CRS-DEA and VRS-DEA specifications (Coelli 2005)

174 We apply the smoothing homogeneous bootstrap approach with 2000 iterations to overcome
175 the potential problem of biased results in our second-stage regressions (for a more in-depth
176 discussion see (Simar & Wilson, 2000 and Simar & Wilson, 2008).

177 **Simar-Wilson bootstrapping regression analysis**

178 In the second stage, the efficiency values estimated in stage one are regressed on some relevant
179 exogenous variables not included in the DEA analysis. According to Liebert & Niemeier (2013)
180 an advantage of second-stage approaches is that explanatory variables are not included in the

181 first-stage of the analysis and, therefore, do not affect the discriminatory power of the first-
182 stage procedures.

183 Simar and Wilson (2007) describe a data generating process under which two-step methods are
184 consistent. Following the Simar and Wilson (2007) approach, the paper assumes and tests the
185 following regression specification:

$$\varphi_j^{VRS} = a + z_j\delta + \varepsilon_j \quad (2)$$

186 which can be understood as the first-order approximation of the unknown true relationship. In
187 Eq. (2), a is the constant term, ε_j is the error term, and z_j is a (row) vector of observation-
188 specific variables for DMU_j that we expect is related to the DMU's efficiency score, φ_j^{VRS} .

189 Based on a truncated-regression with a double bootstrapping procedure, the Simar and Wilson
190 (2007) approach assume that the distribution of ε_j is truncated normal with zero mean, unknown
191 variance, and (left) truncation point determined by this very condition.

192 Eq. (2) is estimated by maximising the corresponding likelihood function concerning δ
193 parameters and the variance of the error term. Algorithm#2 from Simar and Wilson (2007) is
194 applied. For the sake of brevity, we refer the reader to Simar and Wilson (2007) for the details
195 of the bootstrap procedure.

196 The explanatory z -variables used in our model have been chosen as a result of an extensive
197 review of airport literature. Three environmental variables for each airport are measured in
198 terms of: (1) the Logistic Performance Index (*Logistic*)¹; (2) the presence of a High Speed Rail
199 (HSR) station in the airport (*Airport Intermodality*); (3) the rate of Gates with fingers-bridges
200 relative to total Gates (*Jet bridge*).

201 **Data Analysis**

202 The study sample includes the major 21 airports in Europe. The database is a balanced panel
203 observed over the 2009 to 2014 period. All sample airports operate as hubs. The airports
204 included are Amsterdam, Barcelona, Berlin TXL, Brussels, Budapest, Copenhagen, Dublin,
205 Dusseldorf, Frankfurt, Hamburg, Lisbon, London LGW, London LHR, Madrid, Munich, Paris
206 CDG, Paris ORY, Roma FCO, Stockholm ARN, Vienna, and Zurich.

207 The selection of output and input variables for the first stage of our investigation was based on
208 a review of airport efficiency literature. Financial, operational and infrastructure characteristics
209 of the European airports have been used to estimate the airport efficiency.

210 The number of passengers arriving or departing via commercial flights (*Pax*), the amount of
211 cargo shipped (*Cargo*) and the operating revenue (*OpRev*) have been selected as output
212 variables. Selecting the output variables we took into account that the airport industry is a
213 paradigmatic case of joint production (see Yoshida & Fujimoto 2004).

214 Input data include the number of full-time equivalent employees directly employed by the
215 airport (*Labour*), number of gates (*Gates*) and the Intermodal Freight Area (*CargoArea*). Other
216 authors (Coelli et al., 1999, Bazargan & Vasigh, 2003, Sarkis, 2000,...) have previously used
217 these input variables. All input and output variables selected have frequently been used in
218 studies on airport efficiency, as shown in the survey conducted by Liebert & Niemeier, (2013).

219 To undertake this empirical analysis, the airport traffic and technical information were obtained
220 from the information published by each airport operator. The financial data was gathered from
221 the audited financial statements published annually by each airport in their Annual Reports.

¹ The World Bank's Logistics Performance Index (LPI hereinafter) measures the logistic development of countries. The LPI is based on a worldwide survey of ground operators (global freight forwarders and express carriers), providing feedback on the logistics "friendliness" of countries in which they operate and those with which they trade. Performance is evaluated using a 5-point scale and the overall LPI is aggregated as a weighted average of the six areas of logistics performance: Customs, Infrastructure, International Shipments, Logistics Quality, Tracking and Tracing and Timeliness.

222 The data source is the AMADEUS database managed by Bureau van Dijk. The financial data
 223 has been revised and expanded using the corporate website of each entity. All variables
 224 expressed in monetary units have been converted to constant 2009 prices using the CPI
 225 (Consumer Price Index) from the World Bank database. Table 1 summarises the primary
 226 statistics of the sample used in this analysis.

227 **Table 1. Summary statistics of inputs and outputs**

	Variables	Definition and units	Minimum	Maximum	Mean	Standard deviation
	<i>Pax</i>	Number of passengers arriving or departing in thousands	8,081.07	73,405.33	30,875.47	16,596.02
Outputs	<i>Cargo</i>	Amount of cargo in thousands of tons	19.56	2,231.35	440.35	605.54
	<i>OpRev</i>	Turnover in millions of Euros	172.65	3,631.71	773.72	650.54
	<i>Labour</i>	Labour in number of workers	749.00	12,053.00	3,098.00	2,270.00
Inputs	<i>Gates</i>	Total number of boarding gates	17.00	224.00	110.00	61.00
	<i>CargoArea</i>	Intermodal Freight Area in square kilometres	10.00	980.00	178.81	259.23

Source: Own elaboration.

228 Table 2 shows airport ranking by number of passengers and cargo traffic. For example, the
 229 cargo traffic of the main hubs such as London LHR, Paris CDG, Frankfurt and Amsterdam
 230 airports represents almost 70% of the total airport traffic. Meanwhile, the overall passenger
 231 traffic of the four top airports is 36%.

Table 2. Ranking of airports by passengers number and cargo Traffic (2009-2014).

Airports	Passengers (in thousands of)	Passengers (% of total)	Cargo Traffic (Tonnes x 10 ³)	Cargo Traffic (% of total)	Logistic (LPI) (Index)
LONDON LHR	69526.94	0.11	1436.87	0.16	3.95
PARIS CDG	60549.59	0.09	1504.49	0.16	3.84
FRANKFURT	55917.54	0.09	2065.05	0.22	4.09
AMSTERDAM	49476.29	0.08	1525.29	0.16	4.06
MADRID	45644.89	0.07	380.08	0.04	3.67
MUNICH	36825.02	0.06	314.25	0.03	4.09
ROMA FCO	36290.38	0.06	147.12	0.02	3.66
LONDON LGW	34178.41	0.05	95.54	0.01	3.95
BARCELONA	33097.24	0.05	97.27	0.01	3.67
PARIS ORY	26938.31	0.04	69.22	0.01	3.84
ZURICH	24029.28	0.04	309.78	0.03	3.89

COPENHAGUE	22720.21	0.04	164.90	0.02	3.89
VIENNA	20913.80	0.03	226.47	0.02	3.80
DUSSELDORF	20124.70	0.03	85.06	0.01	4.09
DUBLIN	19749.84	0.03	109.43	0.01	3.76
STOCKHOLM ARN	19143.40	0.03	82.77	0.01	3.97
BRUSSELS	18659.32	0.03	420.51	0.05	3.98
BERLIN TXL	17397.83	0.03	29.20	0.00	4.09
LISBON	15275.92	0.02	92.69	0.01	3.45
HAMBURG	13414.99	0.02	28.67	0.00	4.09
BUDAPEST	8511.07	0.01	62.69	0.01	3.18

232 Source: Own elaboration

233

234 Efficiency analysis

235 The DEA approach was used to determine the levels of scale efficiency, pure efficiency, and
236 overall technical efficiency². Table 3 reports average scores (2009-2014) for the three types of
237 efficiency, ranking the airports according to overall technical efficiency. The airports reaching
238 the top levels of technical efficiency are Zurich, Vienna, Frankfurt, Berlin TXL, Amsterdam,
239 and London LGW. The results also show that only one airport (Zurich) is on the efficient
240 frontier for the entire period. Furthermore, the average technical efficiency score is relatively
241 high (0.78), indicating that European airports are achieving optimum airport management
242 proportional to their operating scale.

243 **Table 3. Average scores for the efficiency in airports ranked by overall technical efficiency**

Airports	Technical efficiency (constant returns)	Pure technical efficiency (variable returns)	Scale efficiency
ZURICH	0.99	1.00	0.99
VIENNA	0.97	0.99	0.98
FRANKFURT	0.97	0.97	1.00
BERLIN TXL	0.97	1.00	0.97
AMSTERDAM	0.95	0.95	1.00
LONDON LGW	0.93	0.96	0.97
DUSSELDORF	0.90	0.91	0.99
BRUSSELS	0.89	0.99	0.89
MUNICH	0.86	0.97	0.89
PARIS CDG	0.86	0.93	0.92
ROMA FCO	0.84	0.96	0.88
LONDON LHR	0.83	0.90	0.92

² To mount the potential problem of biased results in the analysis' second-stage, we use the smoothing homogeneous approach with 2000 iteration.

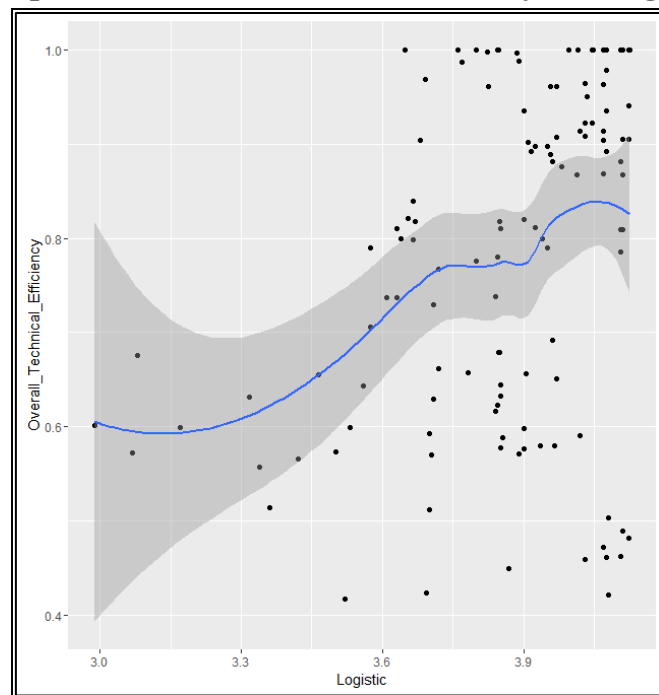
BARCELONA	0.73	0.80	0.92
MADRID	0.70	0.77	0.91
PARIS ORLY	0.67	0.70	0.95
BUDAPEST	0.62	0.93	0.67
COPENHAGUE	0.60	0.61	0.98
STOCKHOLM ARN	0.58	0.59	0.98
LISBON	0.58	0.73	0.79
DUBLIN	0.50	0.53	0.95
HAMBURG	0.47	0.58	0.82

244 Source: Own elaboration.

245 The results show that Dusseldorf, Hamburg, and Budapest operate at the optimal scale. On the
 246 contrary, Madrid, Munich, and Roma FCO operate under decreasing returns to scale. Hence,
 247 these airports' operators should seek opportunities to increase their scale.

248 The findings reported in Table 2 and 3 suggest a positive relation between logistic system
 249 quality and technical efficiency. To corroborate these results, Figures 1 shows the relationship
 250 between the proportion of logistics levels and the overall technical efficiency.

251 **Figure 1. Relationship between overall technical efficiency and Logistics levels**



252
 253 Source: Own elaboration.

254
 255 **Regression analysis**

256 The growing trend of airport competition is challenging airport managers worldwide to provide
 257 the best possible services most efficiently. To achieve this, airports need to be aware of their
 258 performance compares to the industry's best practices.

259 Table 4 displays the estimated numbers of regression models for the 21 airports sample
 260 providing scores for overall technical efficiency, pure technical efficiency, and scale efficiency
 261 as dependent. The truncated regression with a bootstrap model appears to fit the data well, with

262 positive t-statistics, which are statistically significant, in most cases. Parameters with a positive
 263 sign reveal a positive relationship between the corresponding explanatory variable and the
 264 dependent variable.

265 **Table 4. Parameter estimates for the Simar-Wilson regression model**

Explanatory factors	Overall technical efficiency -constant returns to scale- (z-statistic)	Pure technical efficiency -variable returns to scale- (z-statistic)	Scale efficiency - economies of scale- (z-statistic)
Logistic (LPI)	0.15027** 1,95	-0,19331 1,35	0.35362*** 4,95
Airport Intermodality	0.27312*** 3,02	0.58595** 2,42	0.05337 0,71
jet bridge	0.42768*** 3,27	0,55867*** 2,63	0.47360*** 3,28

Notes: ***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively. Likelihood ratio chi-square (df = 2)

266 The results were obtained by an input-oriented model, which assumes that the managers cannot
 267 influence the traffic level in the short-term future. Consequently, the focus should be given to
 268 increase the efficiency levels by enhancing the intermodality and the logistic quality system.
 269 This policy could improve the efficiency of the whole system in the European air infrastructure
 270 in the long-term future.

271 The *logistic* variable is significant to explain the overall technical efficiency and the scale
 272 efficiency with a positive coefficient. The *logistic* variable provides feedback from logistic
 273 operators, supplemented with quantitative data on the performance of the main components of
 274 the logistics chain. The positive sign of the *logistic* variable indicates that airports located in
 275 countries that have higher LPI levels are expected to have higher overall technical efficiency,
 276 and scale efficiency scores compared to the rest of European airports. The economic impact of
 277 national logistics (measured using the LPI) on overall airport efficiency is estimated at 0.15%
 278 for every 1% increase in LPI, ceteris paribus.

279 *Airport Intermodality* variable is significant with a positive coefficient, indicating that airports
 280 with direct linkage between the airport and a High-Speed Rail network are expected to have
 281 higher overall technical efficiency and pure technical efficiency compared to airports without
 282 HSR Station.

283 Our analysis shows that Intermodal Airports (airports linked to a High-Speed Rail network)
 284 were, on average, 23 percent more efficient over the period. These HSR links allow passengers
 285 to substitute short-haul flights for trains. Furthermore, direct HSR link allows airports to
 286 manage their slot capacities better when facing congestion. Direct rail links also increase airport
 287 catchment areas for passengers. However, according to the above results, this type of
 288 intermodality still suffers from a lack of physical integration and interoperability among the
 289 different airports in Europe.

290 The *jet bridge* variable is significant to explain the overall technical efficiency, the pure
 291 technical efficiency and the scale efficiency with a positive coefficient. Therefore, airports with
 292 a higher percentage of Gates with fingers-bridges are expected to perform at a much more
 293 efficient level.

294 The above results are meaningful to policymakers. Supply chains are a complex sequence of
 295 coordinated activities. The performance of the supply chains depends on such government
 296 interventions as infrastructure, logistics services provision, and cross-border trade facilitation.

297 Redirect public expenses toward more efficient investment in the innovation of the logistic
298 process could be advisable in the Air transport sector.

299 There is room for a coordination policy regarding off-airport operations. Better integration of
300 vehicle, ship, rail, and air transport passengers and cargo would be desirable to achieve better
301 airport efficiency. Additionally, airports that are linked to railway networks will have a
302 considerable advantage if participating in an extensive intermodal network. If air traffic is
303 congested in some areas in Europe, it will be advantageous for other airports to redirect traffic
304 demand towards them by rail.

305 The above results are also meaningful to airport managers. The operational performance of an
306 airport is determined by the efficient management of passenger and cargo flows. Optimising
307 the interface between airport and aircraft on all aspects – personal, physical, informational- will
308 reduce aircraft ground time and also will streamline the use of land resources. Investments in
309 logistics innovations should help the management of security checking, boarding & deplaning,
310 personnel processes and terminal processes. Moreover, the development and improvement of
311 hub management strategies should be supported by logistics innovations.

312 These findings are in line with those of Coto-Millán et al. (2015) who estimated the contribution
313 of logistics in domestic technical efficiency and found that the economic impact of logistics on
314 technical efficiency was estimated at 0.59% for every 1% increase in LPI, *ceteris paribus*.

315

316 **Conclusions**

317 Using Data Envelopment Analysis, this paper estimates the Efficiency of the major 21 European
318 airports over the 2009-2014 period. Additionally, in stage 2, applying Simar-Wilson
319 bootstrapping regression analysis, we investigated whether the intermodality and the quality of
320 the national logistics system has a significant influence on the technical and scale efficiency of
321 European airports.

322 This paper contributes to the literature by estimating the contribution of logistics to Airport
323 efficiency. Thus, to the best of our knowledge, this study is the first to document the effect of
324 the national logistics system on Airport productivity.

325 The results highlight the significant impact that the quality of the national logistics system has
326 on Airport efficiency. We show that with a 1% increase in the Logistic Performance Index, the
327 current airport level of overall technical efficiency would improve by 0.15%, *ceteris paribus*.

328 Results highlight the significant impact that the intermodality has on Airport efficiency. Thus,
329 airports with a direct linkage between the airport network and the High-Speed Rail network are
330 expected to have higher overall technical efficiency and pure technical efficiency. The results
331 show that airports that have a direct link to a High-Speed Rail (HSR) network were, on average,
332 23 percent more efficient over the period.

333 The easy of access to the Aircraft another essential factor to explain the efficiency level. Thus,
334 airports that offer more facilities (higher rate of Gates with fingers-bridges) to optimize the
335 interface between airport and aircraft are linked to higher efficiency levels.

336 There are substantive variations in the level of efficiency across Airports in our sample. The
337 results show that only one airport (Zurich) is on the efficient frontier for the entire period. The
338 results also show that the airports of Dusseldorf, Hamburg, and Budapest operate at the optimal
339 scale. However, Madrid, Munich and Rome FCO operate under decreasing returns to scale.
340 Hence, these airports' operators should seek the above opportunities to increase the scale.

341 The above results are meaningful to policymakers. An efficient and integrated multimodal
342 transport system necessarily requires different modes of transportation being seamlessly linked
343 and efficiently combined. Airports do not have control over access to high-speed rail lines. The
344 efficiency of logistics networks depends on government services, investments, policy and

345 strategic planning. Building infrastructure, developing a regulatory regime for transport
346 services, and designing and implementing efficient customs clearance procedures are the areas
347 where governments play an essential role. Effective investment in the innovation of the logistic
348 process could be advisable in the Air transport sector.

349 The above results are also meaningful to airport managers. The operational performance of an
350 airport is determined by the efficient management of passenger and cargo flows. Global supply
351 chains require modern logistics services including innovations in intermodal transport and the
352 application of information technology in physical distribution and materials management.
353 Investments in logistics innovations should help the management of security checks, boarding
354 & deplaning, personnel processes and terminal processes. Moreover, the development and
355 improvement of hub management strategies should be supported by logistics innovations.

356

357 **AUTHOR CONTRIBUTION**

358 X.L.F and J.G. conceived of the presented idea. X.L.F. and J.G. developed the theory and
359 performed the computations. P.C. verified the analytical methods and supervised the findings
360 of this work. All authors discussed the results and contributed to the final manuscript.

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