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Persistent and transient productive efficiency in the African airline industry

Gianmaria Martini*, Università degli studi di Bergamo, Italy, gianmaria.martini@unibg.it
Flavio Porta, Università degli studi di Bergamo, Italy, flavio.porta@unibg.it
Davide Scotti, Università degli studi di Bergamo, Italy, davide.scotti@unibg.it

Abstract

Airline efficiency growth is considered one of the key factors for aviation sustainability in Africa and, in turn, for creating a successful relationship between aviation activities and economic development in the continent. This paper proposes estimating the efficiency of African airlines in the period 2010-2019 using a state-of-the-art stochastic frontier model disentangling persistent, transient efficiency, and unobserved heterogeneity. We also examine the impact of (i) ownership structure, (ii) political stability, and (iii) geographical location exerts on both persistent and transient efficiency, and confirm the importance of the optimal use of durable capital inputs for African airlines. We also find evidence of decreasing returns to scale and of average levels of persistent and transient efficiency relatively low. On the basis of these results, some policy implications are derived and discussed in the direction of increased (i) liberalization and (ii) the presence of private capital in African airlines.

Keywords: Persistent and transient efficiency, African airlines, Stochastic frontier analysis

1 Introduction

It is generally agreed in the literature that the supply-side transportation infrastructure fosters economic development and that this effect is greater the more solid and efficient is the airline industry connected to it. Many studies provide evidence of the relationship between air transport services and regional development. For example, air transport services proved to positively influence (i) the growth of population and employment levels (Blonigen and Cristea, 2012; Green, 2007), (ii) tourist activities (Graham and Dobruszkes, 2019), (iii) agglomeration economies (Rosenthal and Strange, 2001; Glaeser et al., 1992), (iii) foreign direct investment flows (Fageda, 2017), and (iv) international trade (Button et al., 2015).

This connection is crucial for Africa, which is the largest continent on earth, with many landlocked countries, and poor road and railways infrastructures. Unfortunately, African airlines, especially in Sub-Saharan Africa, notoriously suffer from a lack of efficiency due to several reasons. They are relatively small, enjoy little economies of density and scope, face market instability and lack of liberalization, are often subject to considerable political interference, and are characterized by a lack of cooperation (Button et al., 2017, 2022). This explains why airline efficiency growth is considered one of the main paths ahead for aviation sustainability in Africa and, in turn, for creating a successful relationship between aviation activities and economic development in the continent (ADBG, 2019).

A key factor toward economic development, especially in such a context of underdeveloped aviation industry, is represented by policy interventions aimed at removing the conditions that make airlines operate inefficiently. In this regard, Africa is lagging behind other regions in the world like the US and Europe since the deregulation process is still far from being completed, as discussed in detail in Section 3.

This paper proposes estimating the efficiency of African airlines in the period 2010-2019 using a recently developed parametric method (Colombi et al., 2014, 2017) and examining the impact of a set of possible determinants on the estimated scores. More knowledge about the efficiency of the continent's carriers and its determinants is expected to provide African governments and policymakers useful information in improving the industry and consequently enjoying the associated wider economic benefits, especially in the light of the current COVID-19 pandemic, whose impact on African airlines has been really severe (UNECA, 2020).

The paper is organized as follows: Section 2 revises previous contributions on airlines efficiency, Section 3 presents the main features of the African airline industry. Section 4 presents the empirical model, while Section 5 describes the data and provides some descriptive statistics. Section 6 shows our results, and Section 7 performs the diagnostic checks on the microeconomic foundations of the estimated production function. Section 8 concludes the paper with some policy implications.

2 Literature review

Since the 1980s the transportation economics literature studies airline performances with a focus mainly on technical efficiency and total factor productivity (Scotti and Volta, 2017). Heshmati and Kim (2016) and Yu (2016) provide a detailed review of the methodologies and the variables used in this kind of studies. Traditionally, researchers are mainly focused on the factors affecting efficiency and on how technical efficiency and productivity evolve over time (Good et al., 1993, 1995; Oum and Yu, 1995; Alam and Sickles, 1998; Sickles et al., 2002). Some other benchmarking studies investigate airline cost efficiency (Oum and Zhang, 1991; Oum and Yu, 1998; Heshmati et al., 2018), productivity and cost competitiveness (Oum and Yu, 2012; Windle, 1991), or airline profitability (Scotti and Volta, 2017).

Looking specifically at studies focused on technical efficiency (i.e., the subject of our paper), they apply both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The properties of the two approaches are well known by researchers as well as their advantages and disadvantages. Coelli et al. (2005) explains in detail that DEA, as a non-parametric and deterministic approach, does not require any assumption on the functional form of the production function, but measurement errors and other sources of statistical noise are basically ignored. On the contrary, SFA estimates the frontier parametrically thanks to the introduction of a random component error term that captures statistical noise. This of course requires assumptions (i) on the functional form of the production function under study, and (ii) on the statistical distribution of the error term. From the methodological point of view, our paper belongs to the group of parametric studies and applies a quite recent SF model that, as explained in detail in the methodology section, has two main advantages: (i) it avoids confounding time-invariant inefficiency with unobserved heterogeneity, and (ii) it allows to disentangle persistent (long-run/time-invariant) from temporary inefficiency (short-run/time-varying). To the best of our knowledge, the only contribution distinguishing between persistent and transient efficiency applied to the airline industry is (Heshmati et al., 2018). However, this paper is focused on international airlines and cost efficiency, and it applies an estimated method based on Filippini and Greene (2016) approach, which is a simulated maximum likelihood estimation method. No African airlines are included in the data set.[1] The latter is less general than the approach adopted in this paper (Filippini and Greene (2016) exploits the possibility to characterize the four random component model as a pair of two-part disturbances in which each element of the pair has its own skew normal distribution) that is based on Colombi et al. (2014, 2017); in a trade-off between statistical efficiency and estimation time Filippini and Greene (2016) might be useful when the ML estimation method becomes computationally demanding, i.e., for a long time horizon.[2]

Concerning the variables used, there are many. Looking at inputs, it is quite common to observe studies focusing on labor and capital, sometimes combined with material or energy. It is not uncommon also to find, among the inputs selected, monetary variables such as operating costs or fuel expenses. In terms of output, the most used variables are passengers, freight, revenue passenger kilometers, but also monetary variables such as revenues. Among the factors affecting

[1] They find that Asian airlines are more efficient that European and North American ones.

[2] Even if not focused on aviation, another interesting contribution estimating persistent and transient efficiency in Africa is Adom et al. (2018), which studies energy efficiency for African countries.

efficiency, the most considered variables are (i) ownership structure, (ii) fleet characteristics, (iii) network characteristics, and (iv) business-model-related variables such as alliance membership and being a low-cost carrier.

If we look more specifically at the papers on African airlines, apart from some contributions that apply benchmarking analysis to samples including some major airlines in the world, thus also some African carriers (e.g., Merkert and Hensher (2011); Aydın et al. (2020)), our work is more connected to papers studying a sample made entirely of African carriers. To the best of our knowledge, there are only two contributions in the literature of this kind. The first study is Barros and Wanke (2015). The paper uses the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), namely a multiple-criteria decision-making method, to rank 29 African carriers for the period 2010-2013. The inputs considered are the number of employees, the number of aircraft (as a proxy for capital), and the operating costs. The two output variables used are revenue passenger kilometers and revenue tonne-kilometers. The authors also perform a second-stage analysis based on neural network techniques, where they consider as contextual variables some business characteristics (e.g., age of the company and public ownership), network size (number of domestic, intra-African, and international destinations), and the fleet mix in terms of aircraft models. The authors' results show an average low-efficiency score. They also find a positive impact of public ownership on efficiency scores suggesting a linkage between performance and protectionist practices adopted by African governments. Other variables impacting efficiency are network size (the larger the higher the efficiency) and fleet mix. In a second contribution, Barros and Wanke (2016), the same two authors use a two-stage network DEA approach to analyze the same sample. The novelty there is that the production process of African carriers is decomposed into a first stage, where employees and planes are the input variables used to produce destinations (the efficiency of this sub-process is called "network efficiency"), and a second one, where destinations are used to produce financial revenues (the efficiency of this second sub-process is called "operational efficiency"). The resultant efficiency scores exhibit a little variation over time at the airline level, and the average efficiency scores are confirmed low, with revenue efficiency lower than network efficiency. Concerning the environmental factors, neural network results show that public ownership plays a negative role in network efficiency, but a positive role in revenue generation. Years in business are found to affect positively efficiency, while the relevance of airline fleet mix varies depending on the specific aircraft model considered.

Finally, some papers focus on South Africa only, namely Mhlanga et al. (2018); Mhlanga (2019, 2020). Despite the reduced sample, in terms of both geographical focus and size (few airlines and a limited number of years), these papers highlight once again the relevance of the ownership structure as a driver of efficiency. More specifically, Mhlanga et al. (2018) and Mhlanga

(2019) benchmark ten airlines in Southern Africa (period 2012–2016). They combine DEA to a second stage analysis based on a two-way random effects GLS and also Tobit regression. Some of the main results are as follows. State ownership negatively affects technical efficiency as a result of governments' veto power over their airline's commercial choices. Also, LCCs are found more efficient as well as airlines with bigger aircraft and higher load factors. Mhlanga (2020) analyze a sample of nine South African airlines in the period 2015-2018 with a bootstrapped meta-frontier approach. The paper confirms that airline ownership (together with aircraft size and airline cost structure) significantly affects technical efficiency. More specifically, public ownership is found to be negative for efficiency in line with the previous contribution.

Beyond the fact that the African airline industry is understudied compared to more advanced industries like the US and the European ones, and this is especially true for efficiency studies, the main contribution of our paper is as follows: (i) we to study African airline efficiency and some of its determinants through a quite advanced methodological parametric approach, never applied before to the African airline industry, and (ii) our period of the analysis is much longer compared to the existing literature on African airlines. This is why we believe that our findings may have interesting managerial and policy implications contributing to the sustainability of African aviation and reinforcing the relationship between airline services and economic development in African countries.

3 The African airline industry

It is generally recognized that Africa has a great potential for the development of air services. The continent represents a significant portion (about 15%) of the world's population, spread in more than 50 countries, and its geography is characterized by huge distances and increasingly by large urban concentrations (Lubbe and Shornikova, 2017; Button et al., 2015). Despite that, African continental airline markets are quite small (only about 2% of global traffic) and concentrated in a few countries, with most of the airlines that are locally oriented and inefficient (Button et al., 2022). More specifically, African airlines are small, especially in Sub-Saharan Africa, benefit little from economies of scope and density, and, on top of that, are often subjected to considerable political interference. As a result, market instability due to the unprofitability and inefficiency of African carriers is really an issue in an industry that regularly observes airlines entering and leaving the market.

The current COVID-19 pandemic has made things even worse, with Africa constantly lagging behind other regions in terms of vaccine rates. As highlighted by IATA (2021), the pandemic (i) affected tourism and business travel volumes bringing an increase in airlines' losses from -2.7

\$/passenger in 2019 to -44.6 \$/passenger in 2020, and slowing down the recovery (current IATA predictions for 2022 indicate a -21.8 \$/passenger).

Apart from the COVID-19 pandemic, there are many reasons on the basis of the bad economic performances of African airlines. First, is the lack of liberalization. Globally, the liberalization of air passenger services began in the US (Airline Deregulation Act., 1978) followed by Europe (about a decade later). With a little delay, also in Africa, some efforts were made over the last 25 years toward the creation of a multilateral air transportation common market: the Yamoussoukro Decision (YD) in 1999 was the most significant agreement in this direction (Scotti et al., 2017). YD aimed at liberalizing international air travel within Africa, but it did not prove very successful (Lubbe and Shornikova, 2017; Njoya, 2016). As a result, new efforts were required and, in 2018, they materialized in the foundation of a Single African Air Transport Market (SAATM) aimed at accelerating the full implementation of YD (Button et al., 2022). SAATM is currently under implementation, even if still hindered by factors such as the culture of non-prioritization of aviation, and protectionist policies (InterVISTAS, 2021). Other traditional reasons behind the poor performances of African airlines are high (compared to the rest of the world) costs in terms of both fuel and airport charges, old aircraft fleets, the lack of a skilled labor force, the competition from extra-African carriers (European and Gulf airlines), and political instability.

The extreme relevance of these difficulties is not limited to the aviation industry, but to economic development in general. The existing literature indeed agrees on the positive impact exerted on economic growth by aviation development, with benefits observable in terms of trade volumes, income, employment, firm localization, and industrial relations (Manello et al., 2022).

The issue of airline efficiency is therefore extremely important in the African context, and this is even truer in the current context of crisis. African governments appear more and more aware of the wider economic benefits associated with an improved aviation industry and have now more than ever an important opportunity to rethink the future of their inefficient/unprofitable carriers. Indeed, only the most efficient and profitable airlines have a chance to withstand the current tide of passenger restrictions (Thomas, 2020). Hence, identifying efficient airlines and also understanding the drivers of efficiency, we believe, are timely and useful exercises on which the African airline industry can build its own future foundation.

4 Empirical model for African airline efficiency

Our aim is to estimate a production function for African airlines using an SFA with transient efficiency, persistent efficiencies, and unobserved heterogeneity, as in Colombi et al. (2014), and in Colombi et al. (2017). We consider the following airline production frontier model:

$$y_{it} = \beta_0 + \boldsymbol{x}'_{it}\boldsymbol{\beta} + b_i - u_{it} - u_i + e_{it}, \tag{1}$$

where the index $i, i = 1, 2, \ldots, N$, denotes the N African airlines in the sample, and $t, t = 1, 2, \ldots, T$, the T periods at which each airline is observed. The dependent variable y_{it} is the logarithm of airline i's annual number of passengers in period t, $\mathbf{x}'_{it}$ is a row vector of p inputs involved in airline i's production process and β is a column vector of p unknown parameters. The random-airline effect b_i is capturing unobserved heterogeneity, u_{it} is a non-negative random variable for transient efficiency of airline i at period t, u_i is a non-negative random variable for persistent inefficiency, and e_{it} is a normal random variable representing the exogenous shock affecting airline i's number of passengers in period t. We assume that:

(A1) for $i = 1, 2, \ldots, n$, the random variables u_i, b_i and u_{it}, e_{it}, $t = 1, 2, \ldots, T$, are independent in probability. This means that, for each airline, the random components in the model (1) are independent;

(A2) the random vectors $(b_i, u_i, u_{i1}, u_{i2}, ..., u_{iT}, e_{i1}, e_{i2}, ..., e_{iT})$, $i = 1, 2, ..., n$, are independent in probability, i.e., the errors are independent among airlines;

(A3) for $i = 1, 2, \ldots, n$, u_i is a normal random variable, with null expected value and variance σ_u^2, left-truncated at zero, and b_i is a normal random variable with null expected value and variance σ_b^2;

(A4) for $i = 1, 2, \ldots, n$, and $t = 1, 2, ..., T$, u_{it} is a normal random variable, with null expected value and variance σ_{ut}^2, left-truncated at zero and e_{it} is a normal random variable that has null expected value and variance σ_e^2;

(A5) for $i = 1, 2, \ldots, n$, and $t = 1, 2, ..., T$, $\boldsymbol{x'_{it}}$ are row vectors of exogenous variables.

We assume that:

$$v_{it} \sim N(0; \sigma_v^2); u_i \sim N^+(\mu; \sigma_{ui}^2), u_{it} \sim N^+(\varrho, \sigma_{uit}^2), b_i \sim N(\nu; \sigma_b^2)$$

i.e., the random shock component has a normal distribution with mean 0 and variance σ_v^2, the persistent inefficiency random component has half-normal distribution with variance σ_{ui}^2, the transient inefficiency random component has half-normal distribution with variance σ_{uit}^2, while the unobserved heterogeneity random component has mean-variance σ_b^2. The deterministic component given by the terms $\beta_0 + \boldsymbol{x}'_{it}\boldsymbol{\beta}$ is the production function mapping the inputs transformed in each airline to move passengers. The components u_{it} have expected values $\mu_{it} = \sqrt{\frac{2}{\pi}\sigma_{uit}^2}$ that depend on a set of variables (exogenous determinants of the transient inefficiency) through the linear model:

$$ln(\sigma_{uit}^2) = \gamma_0 + \boldsymbol{z}'_{it}\boldsymbol{\gamma}, \tag{2}$$

where $ln(\sigma_{uit}^2)$ is the logarithm of the transient inefficiency variance, $\boldsymbol{z}'_{it}$ is a row vector of q exogenous determinants of transient inefficiency and $\boldsymbol{\gamma}$ is a column vector of q unknown parameters. Moreover, the persistent inefficiency components u_i have expected value $\mu_i = \sqrt{\frac{2}{\pi}\sigma_{ui}^2}$ that depends on exogenous determinants through the following linear model:

$$ln(\sigma_{ui}^2) = \delta_0 + \boldsymbol{w}'_i\boldsymbol{\delta}, \tag{3}$$

where $ln(\sigma_{ui}^2)$ is the logarithm of the persistent inefficiency variance, $\boldsymbol{w}'_i$ is a row vector of q' exogenous determinants of transient inefficiency and $\boldsymbol{\delta}$ a column vector of q' parameters.[3]

We fit model (1) with the additional equations (2)–(3) for the determinants of efficiencies under two functional specifications: (1) Cobb-Douglas; (2) translog.[4] The equation representing the translog airline production function is:

$$\ln(y_{it}) = \beta_0 + \sum_{k=1}^{p} \beta_k \ln(x_{it}) + \frac{1}{2}\sum_{k=1}^{p}\sum_{j=1}^{p} \beta_{kj} \ln(x_{kit}) \ln(x_{jit}) + b_i - u_{it} - u_i + e_{it} \tag{4}$$

where $\beta_{kj} = \beta_{jk}$. The translog production function collapses to the Cobb-Douglas production function if $\beta_{kj} = 0, j = 1, 2, ..., p, k = 1, 2, 3, ...p$. One of the main assumptions of model 1 is that unobserved heterogeneity is uncorrelated with the frontier regressors. In order to have control over this assumption, we implement the Mundlak (1978) approach. We add to Eq. (4) the means over time of the time-varying input variables: $\overline{x}_i = \frac{1}{T}\sum_{t=1}^{T} \ln x_{it}$, so that we can rewrite Eq. (4) as follows:

$$\ln(y_{it}) = \beta_0 + \sum_{k=1}^{p} \beta_k \ln(x_{it}) + \frac{1}{2}\sum_{k=1}^{p}\sum_{j=1}^{p} \beta_{kj} \ln(x_{kit}) \ln(x_{jit})$$

[3] As shown by Colombi et al. (2014), Proposition 1, under assumptions (A1)–(A5), the vectors of outputs $\boldsymbol{y}_i = (y_{i1}, y_{i2}..., y_{iT})'$, $i = 1, 2, ..., n$, are independent and have a Closed Skew Normal (CSN) density. The maximization of the log-likelihood of model (1) and ML estimators are discussed in Colombi et al. (2014), Proposition 2, who also showed (Proposition 3) how to compute the efficiency scores $E[\exp(-u_i)|\boldsymbol{y}_i)]$ and $E[\exp(-u_{it})|\boldsymbol{y}_i)]$ for each airline i and period t.

[4] The Cobb-Douglas production function is popular and easier to estimate (fewer parameters involved). However, it has low flexibility since the input elasticity of substitution (i.e., the ratio between two input and their marginal products) is fixed.

$$+\sum_{k=1}^{p}\delta_k\overline{x}_{ki}+b_i-u_{it}-u_i+e_{it} \quad (5)$$

We test the joint significance of the Mundlak terms on the basis of a likelihood ratio test. The Cobb-Douglas production function has output-input elasticities given by the first-order coefficients, i.e., $\epsilon_{y,k}=\beta_k$. In the translog production function these elasticities depend instead on the level of the inputs, i.e., $\epsilon_{y,k}=\beta_k+\sum_{j=1}^{p}\beta_{kj}\ln(x_{jit})$.

Other popular SF models for panel data are nested in model 1. For instance, the time-invariant Pitt and Lee (1981) model is obtained by dropping the random components u_{it}, and b_i from (1). Since Colombi et al. (2014) persistent and transient inefficiency SF model is based on random components, we will compare its estimates with those obtained with a true random effect (TRE) SF model (Greene, 2005b,a), which is obtained by dropping the random term u_i from model (1).

In the available data, each airline has two inputs, labor, and capital; labor is given by the annual number of employees (pilots, flight attendances, ground); capital is related to maximum passenger transport capacity, i.e., the seats available in the airline's fleet. This measure of capital incorporates the size of the aircraft in the airline fleet, information that is instead ignored by contributions using simply the number of planes. Regarding the possible determinants of the two inefficiency terms in (2)–(3), we investigate the impact on airlines efficiency of three factors: airline ownership, the political stability of the country where the airline headquarters is located, and whether the headquarter is in a sub-Saharan country. Ownership is a dummy variable equal to 1 if the local government has more than 50% of the airline shares: in this case, we classify the airline as one with public ownership. The country's level of political stability is a continuous variable given by a World Bank index. Africa is a continent where *coups d'état* frequently occur, and where political systems are often very fragile, not guaranteeing stability for government formations. These factors may not favor airline efficiency strategies, in favor of protectionism. Last, sub-Sahara is a dummy variable equal to one if the reference country for the airline is located South of the Sahara desert. Sub-Saharan countries differ from Egypt, Libya, Algeria, Tunisia, and Morocco, which are on the Mediterranean sea, and benefit from greater possibilities of exchange with the European countries, especially those of Southern Europe. This could have an effect on airlines in this African region seeking efficiency.

Therefore we implement the following econometric model (1) to estimate the production frontier and the efficiency of African airlines:

$$\log(PAX)_{it}=\beta_0+\beta_1\times\log(K)_{it}+\beta_2\times\log(L)_{it}+\delta\times BETWEEN_{it}+b_i-u_{it}-u_i+e_{it} \quad (6)$$

$$\log(u_i) = \delta_0 + \delta_1 \times PUB_{it} + \delta_2 \times POLSTAB_{it} + \delta_3 \times SUBSAHARA_i \tag{7}$$

$$\log(u_{ii}) = \gamma_0 + \gamma_1 \times PUB_{it} + \gamma_2 \times POLSTAB_{it} + \gamma_3 \times SUBSAHARA_i \tag{8}$$

where (6) is the Cobb-Douglas production frontier, which can be augmented by including the Mundlax correction terms $\overline{\log(K)_{it}}$, $\overline{\log(L)_{it}}$, and by adding the quadratic and interaction terms for the translog specification (i.e., $(\log(K)_{it})^2), (\log(L)_{it})^2), \log(K)_{it} \times \log(L)_{it})$. The production frontier has a potential shifter, $BETWEEN_{it}$, which is a variable indicating the centralization of airline i's route network in Africa in period t. Between centralization might capture how close is an airline network to a H&S structure; hence it may have an impact on traffic. Indeed, a H&S system serves more destinations than any alternative network system, being equal to the number of routes operated, and has implications in terms of market size (Button, 2002; Cook and Goodwin, 2008). For these reasons, we believe it has to be incorporated into the analysis as a potential shifter of the output level.

5 The data

Data on the African aviation market are less comprehensive than for US and European, or even Asian, markets. To estimate the model presented in Eqn. (6)–(8) we build a new data set regarding carriers members of the African Airlines Association (AFRAA)[5] for the period 2010-19, i.e., 10 years. The data set relates to the major African airlines and is constructed from different sources. Much of the data used here are from the AFRAA annual reports supplemented from other official and website sources.[6] The betweenness centralization variable is an index computed starting from the Official Airline Guide (OAG), while other variables are obtained from different sources (e.g., political stability is taken from the World Bank. The data mining process results in a balanced panel data set including airline-year data of 17 major African carriers in 10 years (i.e., 170 observations). We download all the annual reports released by AFRAA from 2011 to 2020[7] in order to get the number of passengers, employees, ownership, and fleet details. Then we matched the fleet with the capacity of each aircraft from OAG to express the size of the fleet (K_{it}) in terms of available seats. This measure provides a better estimate than simply counting the number of aircraft because it takes into account also their size.

[5]The Association members represent over 85% of total international traffic carried by African airlines (AFRAA, 2020).

[6]We imputed missing data by interpolating the values of previous and following years and integrating data from the Official Airline Guide (OAG).

[7]each report refers to the previous year data.

Table 1 presents the descriptive statistics of our sample. According to AFRAA, on average African carriers moved 2.8 million passengers per year (PAX_{it}), ranging from 46,851 carried by *Asky Airlines* in 2011 to almost 13 million by *Ethiopian Airlines* in 2019. The standard deviation higher than the mean indicates that there is a relevant variation in size among African carriers. The representative airline fleet consists of 4,592 seats (K_{it}), with a minimum of 185 seats and a maximum of 23,855. Average employment is 7,217 people (L_{it}); again standard deviation is rather high, the minimum is only 203 employees, the maximum 56,400. In the estimates, PAX_{it}, K_{it}, and L_{it} are mean scaled using the geometric mean to standardize the variables and reduce the impact of possible outliers.

Betweenness centralization is the variable that captures the airline network structure. Network measures are important indicators to describe the characteristics of air networks and are currently used in different contributions (e.g., Ciliberto et al. (2019), Roucolle et al. (2020)). In particular, centralization is a measure at the network level that is built by aggregating in a unique index the centrality measures of all the nodes (airports) in an airline network. More specifically, in the case of betweenness, an airport centrality is higher the higher the proportion of shortest routes between pairs of airports on which the airport of interest acts as an intermediate stop. For an airport i, betweenness centrality at time t, C^{it}, is computed as shown in eq. (9) for the node i

$$C_{it} = \sum_{j \neq i \neq k} \frac{\psi^i_{jk}}{\psi_{jk}} \tag{9}$$

where ψ^i is the number of shortest paths between j and k on which i acts as an intermediate stop; ψ_{jk} is the total number of shortest paths between j and k. Betweenness centralization is a measure of how much a network is centralized in its most central node. It is computed as shown in eq. (10), where the numerator is the sum of the differences between the betweenness centrality of the most central airport in the network and the betweenness centrality of all the other airports in the network, while the denominator is the maximum theoretical value of such difference in a network with N nodes, namely the one of a pure hub and spoke (star) network.

$$BETWEEN_{it} = \frac{\sum_{i=1}^{N} C_B^* - C_B^i}{N-1} \tag{10}$$

$BETWEEN_{it}$ is computed using the information on each carrier's airport pairs extracted from the OAG schedule analyzer.[8] Betwenness centralization has an average equal to 0.83 ($BETWEEN_{it}$), it ranges from 0.34 of *LAM Mozambique* to 1 of *Air Seychelles*.[9]

[8]We consider routes having, on average, at least one flight per week in a year.

[9]Almost all flights of *Air Seychelles* originate or land in Seychelles International Airport.

Variable	Mean	S.d.	Min	Max	Unit	Description
PAX_{it}	2,772	2,907	47	12,631	,000	# of annual passengers
K_{it}	4,592	4,951	185	23,855	number	# of annual seats
L_{it}	7,217	12,066	203	56,400	number	flight and ground personnel
$BETWEEN_{it}$	.83	.18	.34	1	Index	Centralization of airline network
PUB_{it}	.82		0	1	dummy	Public control
$POLSTAB_{it}$	3.00	.79	1.62	4.41	Index	Country political stability
$SUBSAHARA_i$	.76		0	1	dummy	Sub-Saharan country

Table 1: Descriptive statistics

$POLSTAB_{it}$ is the World Bank indicator that indicates Political Stability and Absence of Violence/Terrorism and measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. The variable is re-scaled to be positive and greater than one, since it is subject to a logarithmic transformation, and its mean is equal to 3, with a minimum equal to 1.62 (Ethiopia) and a maximum equal to 4.41 (Botswana).

PUB_{it} is a dummy variable that takes value one if the majority of the ownership is public, and 0 otherwise: in our sample, 82% of observations are related to a public ownership airline. $SUBSAHARA_i$ is a dummy variable equal to 1 if the carrier is located in a Sub-Saharan country, and 0 otherwise. About 76% of African airlines in our sample are located in sub-Saharan Africa. (Button et al. (2022) confirm that there is an important geographical separation in air transportation between Mediterranean countries and those South of the Sahara desert, many of which are landlocked.

6 Empirical results

The estimates of African airlines' production frontier and determinants of inefficiency are reported in Table 2, which is split into two parts. The top rows display the estimated coefficients of the inputs K and L and of the production shifter ($BETWEEN$). The heading, in this case, is given by the dependent variable, i.e., $\log(PAX)$. The bottom rows show instead the estimated coefficients of the factors affecting inefficiency. Columns (1)-(4) present the results of Greene (2005a,b) TRE model. In this case, only time-varying inefficiency is included, and the estimated coefficients of $PUB, POLSTAB, SUBSAHARA$ are reported at the bottom rows of Table 2. Columns (5)-(8) show the estimates of Colombi et al. (2014) four random components SF model, that considers both time-varying and time-invariant inefficiencies. The impacts of the factors affecting time-invariant inefficiency are displayed above those related to time-varying inefficiencies. Table 2 presents estimates both for the Cobb-Douglas production function (columns (1)-(2), and (5)-(6)) and for the translog one (columns (3)-(4), and (7)-(8)). The difference in each pair of columns is given by the inclusion in the estimated model of the Mundlak correction variables $(\overline{\log(K)}, \overline{\log(L)})$. The likelihood-ratio test shows that the Mundlak correction variables are an important improvement in the model fit under the translog functional form (the statistics are 19.1, and the p-value is 0.0001), but not with the Cobb-Douglas specification.

	Dependent variable: $\log(PAX)$							
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(K)$	0.6184***	0.5906***	0.5542***	0.4960***	0.6332***	0.5275***	0.6241***	0.5056***
	(0.0501)	(0.0733)	(0.0593)	(0.0536)	(0.0147)	(0.0531)	(0.0188)	(0.0522)
$\log(L)$	0.1795***	0.1423*	0.2458***	0.0971'	0.1723***	0.1408***	0.1325***	0.0676***
	(0.0404)	(0.0602)	(0.0418)	(0.0521)	(0.0249)	(0.0425)	(0.0701)	(0.0185)
$BETWEEN$	0.1929	0.1670	0.1611	0.1911'	0.1831***	0.1688	0.2012	0.2082***
	(0.1544)	(0.1503)	(0.1383)	(0.1109)	(0.0311)	(0.1075)	(0.2567)	(0.0560)
$\overline{\log(K)}$		0.0099		0.0974		0.1513***		0.0806***
		(0.0996)		(0.0753)		(0.0698)		(0.0210)
$\overline{\log(L)}$		0.0840		0.2517***		0.0609		0.2203***
		(0.0798)		(0.0720)		(0.0457)		(0.0277)
$(\log(K))^2$			0.0521	0.1251			0.0712	0.0264
			(0.1162)	(0.0914)			(0.0570)	(0.0256)
$(\log(L))^2$			-0.0860	-0.2178***			-0.0490'	-0.2045***
			(0.1024)	(0.0747)			(0.0256)	(0.0295)
$\log(K) \times \log(L)$			0.0746	0.0119			-0.0714)	0.0871***
			(0.1906)	(0.1624)			(0.0547)	(0.0210)
Constant	0.0625	0.0842	0.0629	0.2716**	0.1343***	0.1846***	0.6470	0.6029***
	(0.1433)	(0.1267)	(0.1383)	(0.1049)	(0.0233)	(0.0348)	(0.1571)	(0.0474)
	Factors affecting inefficiency							
	Time invariant inefficiency							
Determinants of inefficiency								
PUB					-5.7111***	-2.0045***	-2.0844***	-1.5571***
					(0.0210)	(0.0581)	(0.0663)	(0.0224)
$POLSTAB$					4.9012***	1.5376***	1.9592***	1.4785***
					(0.0285)	(0.1427)	(0.1524)	(0.0342)
$SUBSAHARA$					-5.5309***	-3.3612***	2.3659***	1.4037***
					(0.0247)	(0.1089)	(0.0585)	(0.0463)
Constant					-14.8287***	-14.1103***	-3.5270***	-2.8551***
					(0.0404)	(0.0605)	(0.1569)	(0.0456)
	Time-varying inefficiency							
PUB	-1.3531***	-1.3199***	-1.2298***	-0.8132*	-1.3291***	-1.1088***	-0.9654***	-0.8918***
	(0.3903)	(0.3780)	(0.3949)	(0.3223)	(0.0388)	(0.1292)	(0.1115)	(0.0360)
$POLSTAB$	0.5786	0.2889	0.6885	-0.3701	0.4828***	-0.5984***	-0.7775***	-1.6218***
	(0.8457)	(0.8588)	(1.1045)	(0.5784)	(0.0192)	(0.0873)	(0.2202)	(0.0415)
$SUBSAHARA$	32.1002	35.9882	1.6258'	1.9565***	4.1870***	1.7461***	1.8896***	2.3723***
	(-676.9505)	(1178.701)	(0.9111)	(0.3850)	(0.0141)	((0.0725)	(0.0214)	(0.0168)
Constant	-33.7183	-37.2849	-3.4391*	-2.5153***	-2.0726***	0.3770***	4.1430***	-5.8795***
	(-676.9487)	(1178.702)	(1.6796)	(0.6110)	(0.0292)	(0.0370)	(0.1761)	(0.0333)
log-likelihood	1.0426	1.7039	-0.7545	8.7949	-0.2585	2.2373	4.7007	6.8082

Notes: variables with overbar are Mundlak corrections.

Legend: *** 0.1% significance level, ** 1% significance level, * 5% significance level, ' 10% significance level

Table 2: African airlines production frontier and determinants of transient and permanent inefficiency

The results on the deterministic part of the estimated translog SF models (column (8)) confirm that the four-random components approach provides better results. The estimated coefficients are almost all statistically significant. First-order input coefficients $\log K, \log L$ are both positive and statistically significant, as well as those related to the Mundlak correction variables $\overline{\log K}, \overline{\log L}$. The second-order estimated coefficient for labor input is negative (-0.2045) and significant, while that of the input interaction variable $\log K \times \log L$ is positive (0.0871) and significant. First-order input coefficients are positive and significant also with the TRE Cobb-Douglas model (columns (1)-(2)), with the TRE translog model (columns (3)-(4), weakly significant $\log L$ in column (4)), with the Cobb-Douglas four random components model (columns (5)-(6)), and with the four random components model without Mundlak corrections.

Interestingly, the estimated coefficient of the production function shifter $BETWEEN$ is positive and significant with model (1) (column (8)), and equal to $+0.2082$. This confirms that airlines with a H&S route network have higher passenger traffic. A positive estimated coefficient for the network centralization is obtained with the four-random component Cobb-Douglas model without Mundlak corrections.

By splitting airlines' inefficiency into persistent (u_i) and transient (u_{it}), and by separating unobserved heterogeneity from them, as in (Colombi et al., 2014), we obtain better results also regarding the factors affecting the different inefficiency types, as shown in columns (5)-(8) of Table 2, bottom rows. The TRE model identifies only that if the airline has public ownership the transient inefficiency is lower, and sparse evidence (i.e., only with translog production function– columns (3)-(4), and with weak statistical significance if there are no Mundlax corrections in the production function) that if it is located in sub-Sahara the time-varying inefficiency is higher.

The four random component model identifies instead the following results. Public ownership (PUB) always decreases inefficiency, both persistent and transient. This finding confirms previous evidence on African airlines and is countertrend compared with what observed in more developed air transport markets. Our evidence is even stronger than that provided in the existing literature because the results show that both persistent and transient efficiencies are positively affected by public ownership. This result must be interpreted carefully, especially in a policy perspective. In line with Barros and Wanke (2015), we believe that this condition is linked to protectionism and lack of liberalization, namely factors creating an unfavorable environment for genuine competition. In other words, our results suggest that there are not the right conditions, at the moment, for successful private investments in airlines and low cost carriers' development, i.e., for elements that proved to be extremely beneficial in more developed air transport markets.

Higher political stability ($POLSTAB$) improves time-varying inefficiency, while it increases persistent inefficiency. This result may appear surprising in a way. As pointed out by Colombi et al. (2017), persistent inefficiency is mainly due to long-run moral hazard, e.g., obsolete equipment that is not substituted. In air transportation may be due to an aircraft fleet not being adequate to the demand, for which often the available seats are in excess, leading to low load factors; or too much personnel. Since political stability is an indicator linked to government violent overturns, and since it is not rare in Africa the presence of political power concentrated in the hands of a single person, and for a long time, this may lead to political interference in airline employment levels and lower incentives in the efficient use of capital. On the contrary political stability improves short-run inefficiency, providing incentives to limit short-run moral hazard behavior, e.g., inefficient supplier selection and sub-optimal resource allocation, or trial-and-error processes in unknown situations.

Last, still with reference to our main results (column (8) of Table 2), airlines located in sub-Sahara countries have both higher persistent and transient inefficiencies. As expected, airlines closer to Europe benefit from higher influences and transactions with European countries, they are also operating under an open sky agreement (e.g., Morocco and Tunisia signed agreements under the European Neighborhood Policy, that aims to increase economic integration between European Union members and surrounding countries (Bernardo and Fageda, 2017)), and this higher level of competition provides incentives toward lower inefficiency levels.

From the estimated frontier we can compute the efficiency scores of each African airline. Our main results are those shown in column (8) of Table 2; hence, we compute the efficiency scores according to Colombi et al. (2014). Figure 1 shows the details and the dynamics of each airline's efficiency scores during the period 2010-2019, separated by persistent (red) and transient (blu) efficiency.

Some interesting insights are derived from the analysis of efficiency scores. At least four African airlines (i.e., *Egyptair* (MS), *Precision Air* (PW), *Air Algérie* (AH), and *Royal Air Maroc* (AT)), while six airlines have persistent efficiency always lower than transient efficiency (i.e., *Air Namibia* (SW), *Air Seychelles* (HM), *Air Magadascar* (MD), *Air Mauritius* (MK), *Taag Angola* (DT), and *Ethiopian Airlines* (ET)): The other 7 airlines have years where persistent efficiency is higher than transient one, and vice-versa. Regarding transient efficiency, some airlines are improving it during the observed period, as shown by an upward trend in Figure 1: *RwandAir* (WB), *Air Seychelles* (HM), *Asky Airline* (KP), *Kenya Airways* (KQ), *Air Mauritius* (MK), *Air Algérie* (AH), *Royal Air Maroc* (AT), and *Ethiopian Airlines* (ET). *Air Namibia* (SW), and *Air Magadascar* (MD) have instead decreased their transient efficiency levels over the observed period, while all other African airlines have at the end of the period about the same transient efficiency they had at the beginning.

Table 3 provides the details of the distribution of the efficiency scores by efficiency types and by different levels of the factors affecting airlines' technical performances. The first two rows of Table 3 show the descriptive statistics of persistent and transient efficiency scores: the latter (80%) is on average higher than the former (72%). Transient efficiency, on average, is about 73% at the beginning of the observed decade (2010), goes up to 85% in 2017, and stays more or less at that level until the end of the period (0.86% in 2019). These are of course relative level of efficiency, but indicate that diffused technical inefficiency is an issue that should be addressed by proper policy interventions in the industry.

Based on the $1st$ and $3rd$ quartiles of the distribution we identify three categories of airlines' technical performances: inefficient if the score is lower than the median, moderate if the efficiency score is between the median and the $3rd$ quartile, and efficient if the score is higher than the $3rd$ quartile. Regarding persistent efficiency, out of 170 observations, 46% are in the inefficient group and are related to public airlines, while 18% are in the efficient group and are also with public ownership. Private airlines have more observations in the efficient group. Countries with low political stability (the raw index is below 0) have 21% of observations in the inefficient group, 21% in moderate efficiency, and 28% in the efficient category. Countries with high political stability have airlines with 26.5% of observations in the inefficient group, and only 2% and 1% in the moderate and efficient categories. Countries in the sub-Saharan part of Africa have 46% of observations in the inefficient group, 18% in the moderate category, and only 12% in the efficient one. Countries on the Mediterranean sea have airlines with more observations in the efficient group (18%), and only 6% in the moderate category.

Regarding transient efficiency, 22% of public airlines' scores are in the efficient group, as well as in the moderate category; private airlines have more observations in the inefficient category (12%, against 5% in each of the other two categories). If there is low political stability in the countries airlines have 35% of observation in the inefficient group, 18% in the moderate category, and 17% in the efficient one. Countries with high political stability have airlines with 15% of observations falling in the inefficient group, 7% in the moderate category, and 8% in the efficient one. Last, countries in sub-Sahara have airlines with 44% of observations in the inefficient group, 14% in moderate, and 18% in efficient categories.

7 Micro-foundations of estimated production function

In this Section, we check to what extent the estimated production function of African airlines fulfills the well-known properties of Microeconomics production theory, and we draw some consequences in terms of output elasticities, inputs substitutability, and if there are possible benefits arising from production scale.

Efficiency	Min	$1st$ quartile	Median	Mean	$3rd$ quartile	Max
Persistent	0.43	0.52	0.78	0.72	0.86	0.97
Transient	0.12	0.77	0.84	0.80	0.89	0.96
Dynamics of transient average efficiency						
2010	2011	2012	2015	2017	2018	2019
0.73	0.72	0.82	0.78	0.85	0.86	0.86
Number of persistent efficiency scores in different categories						
	Public	Private				
Inefficient	80 (46%)	0 (0%)				
Moderate	30 (18%)	10 (6%)				
Efficient	30 (18%)	20 (12%)				
	Low $POLSTAB$	High $POLSTAB$				
Inefficient	36 (21%)	44 (26.5%)				
Moderate	36 (21%)	4 (2.5%)				
Efficient	48 (28%)	2 (1%)				
	$SUBSAHARA = 0$	$SUBSAHARA = 1$				
Inefficient	0 (0%)	80 (46%)				
Moderate	10 (6%)	30 (18%)				
Efficient	30 (18%)	20 (12%)				
Number of transient efficiency scores in different categories						
	Public	Private				
Inefficient	65 (38%)	20 (12%)				
Moderate	37 (22%)	5 (3%)				
Efficient	38 (22%)	5 (3%)				
	Low $POLSTAB$	High $POLSTAB$				
Inefficient	60 (35%)	25 (15%)				
Moderate	31 (18%)	11 (7%)				
Efficient	29 (17%)	14 (8%)				
	$SUBSAHARA = 0$	$SUBSAHARA = 1$				
Inefficient	11 (7%)	74 (44%)				
Moderate	16 (9%)	26 (14%)				
Efficient	13 (8%)	30 (18%)				

Table 3: African airlines' efficiency scores by efficiency types and exogenous factors

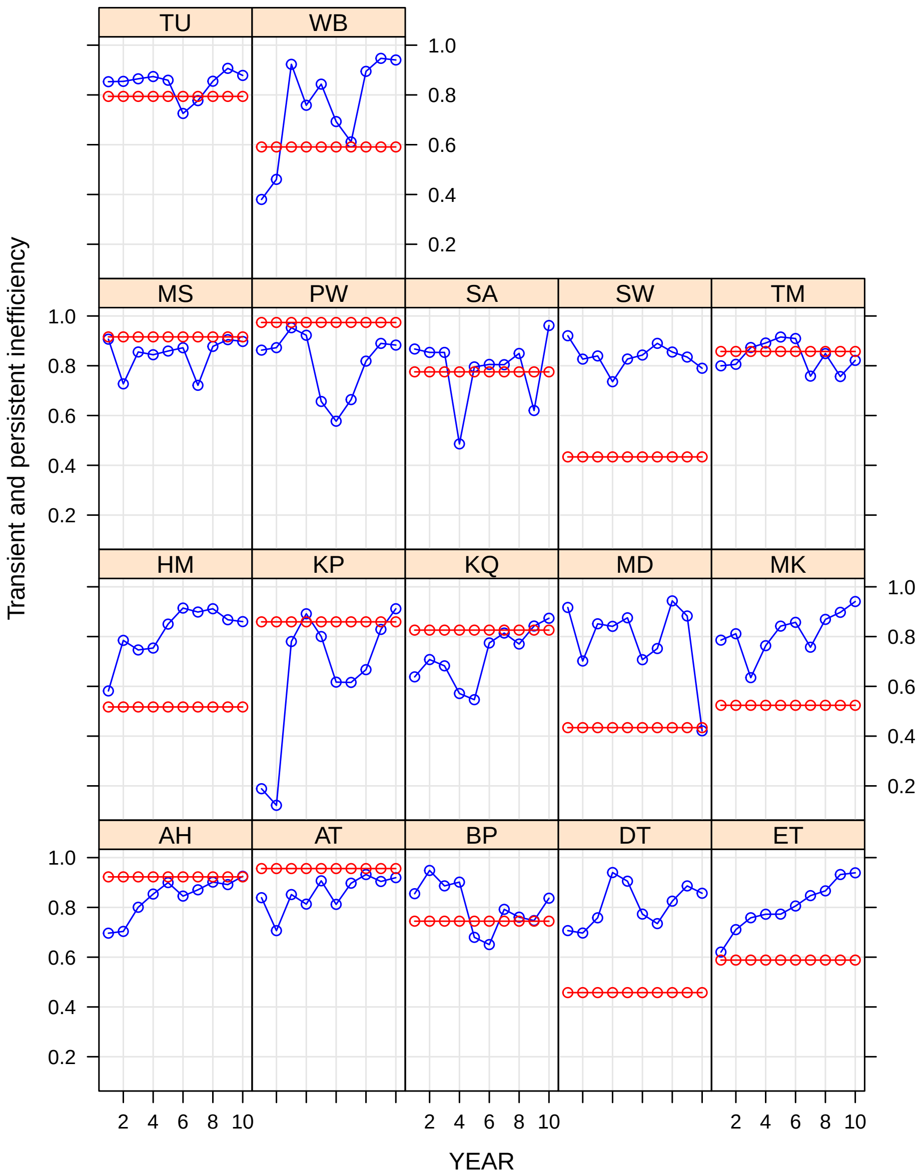

Figure 1: Persistent and transient efficiency in African airlines

Figure 2 presents the distribution of estimated output elasticities of K and L in African airlines, using the results from column (8) of Table 2, i.e., the SF model with two inefficiency types and latent heterogeneity. Regarding the output elasticity of capital, all observations fulfill the monotonicity condition between inputs and passengers. As shown in the right panel of Figure 2, 103 observations out of 170 (61%), have positive output elasticity of labor, while 37% of observations have negative estimates. Regarding input quasi-concavity of the estimated production function, it is necessary to compute the Hessian matrix of second derivatives with respect to K and L, and check, for each observation, that such matrix is negative semi-definite. A sufficient condition, in this case, is that the principal minor of the Hessian matrix is non-positive and all the following minors alternate in sign. This condition is fulfilled in 154 observations out of 170 (about 91% of the full sample). Hence we may argue that for a rather high proportion of observations the estimated African airlines' production frontier shows robust microeconomic foundations.

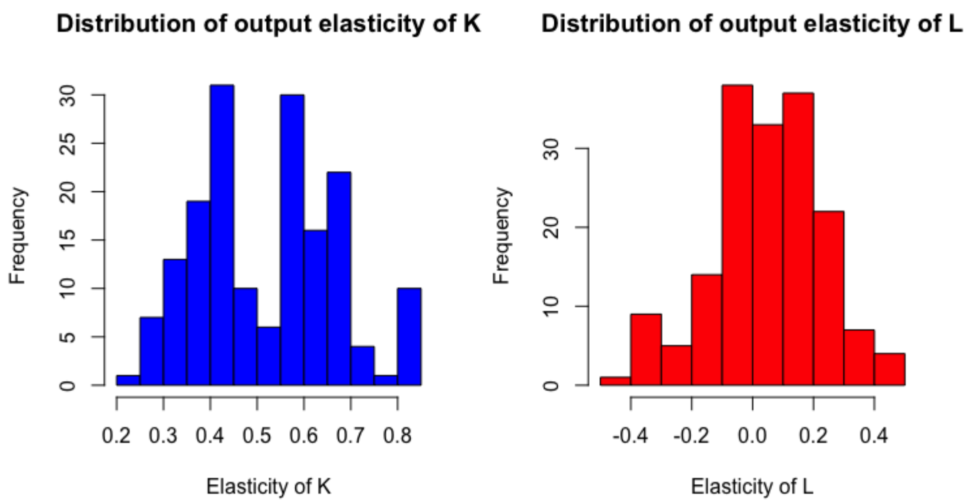

Figure 2: Production function monotonicity condition in African airlines

Being the output and inputs of the estimated production function mean scaled, the first-order estimated coefficients $\log(K), \log(L)$ represent the overall output elasticity of capital and labor respectively. This implies that a +1% in the capital (i.e., fleet capacity) gives rise to +0.51% of passengers, while the same percentage increase in labor force generates an upward shift in annual passengers equal to +0.07%. Figure 3 displays the distribution of the marginal product of K and L in African airlines computed for each observation in our sample. While the marginal product of capital is always positive, for some observations we have a negative marginal product of labor (a similar pattern to that observed for output elasticity of labor). This evidence may be explained by the inefficient use of personnel, maybe due to political reasons.

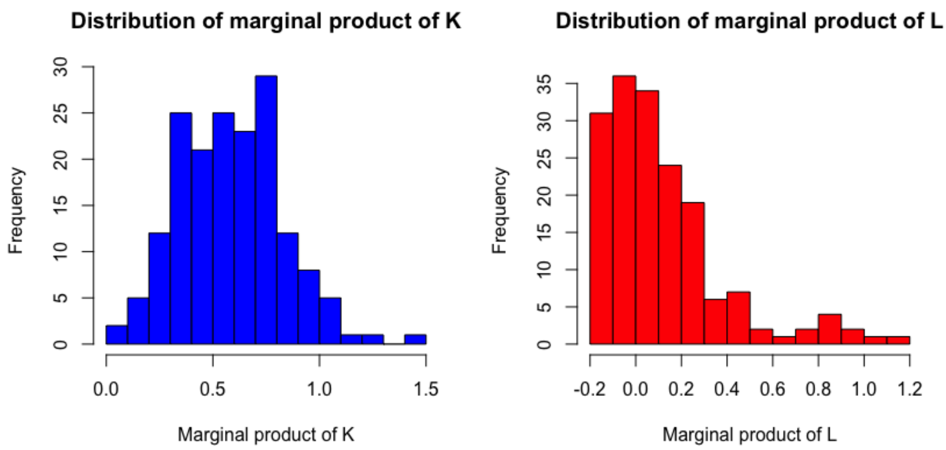

Figure 3: Marginal products of K and L in African airlines

Figure 4 left panel presents the distribution of the estimated scale efficiency. On average it is equal to 0.57, and the maximum estimated value of scale elasticity is equal to 0.78. This implies that African airlines are operating under decreasing returns to scale, i.e., there is an amount of extra capacity and additional use of labor in this continent's air transportation sector.

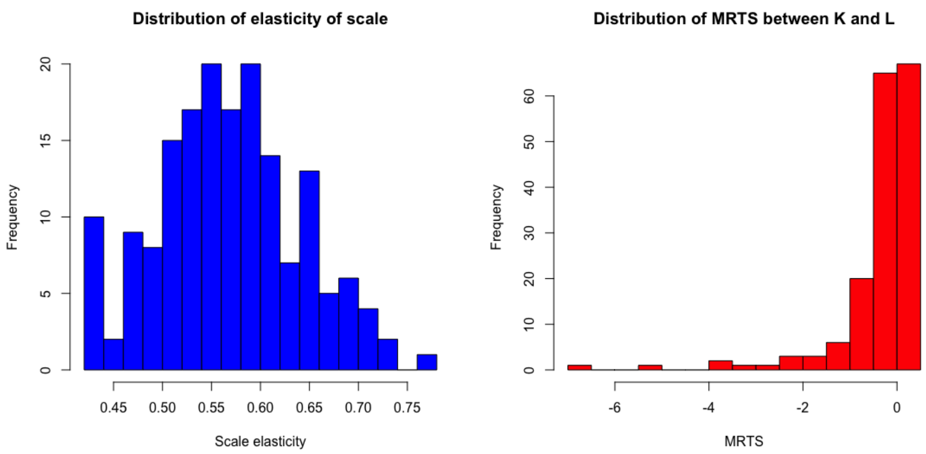

Figure 4: Scale efficiency and $MRTS_{it}$ in African airlines

From the estimated production function we can get the marginal rate of technical substitution ($MRTS_{KL}$) between labor and capital in the African airlines. The right panel of Figure 4 displays the distribution of the marginal rate of technical substitution between capital and labor in our sample. The average $MRTS_{KL}$ is equal to -0.39, while the relative $MRTS_{KL}$ is equal to -0.20. These averages imply that if an airline wants to increase the use of labor by one unit, it has to reduce the use of capital by 0.39 units. The relative marginal rate of technical substitution is the negative ratio between the two output elasticities, in this case with the labor elasticity at the numerator. It means that if an airline aims at increasing labor by 1% it should reduce capital by 0.2%. The estimated $MRTS_{KL}$ is positive for 103 out of 170 observations (61%). The remaining observations are not efficiently using the inputs, given that they exhibit inputs' complementary rather than substitutability. Last, we can analyze the estimated elasticity of substitution, by computing the direct elasticity of substitution.[10]

Last, from the estimated production frontier we compute the direct elasticity of substitution.[11] The average value in the observed sample is equal to 1.15; hence we observe, in the representative African airline, that capital and labor are substitutes.

8 Conclusions

In this paper, we estimate the technical efficiency of 17 African airlines during the period 2010-2019, i.e., before the crisis due to the COVID-19 outbreak. The production frontier is identified by implementing a state-of-the-art stochastic frontier model (Colombi et al., 2014, 2017) that has the error term decomposed into four random effect components: time-invariant persistent inefficiency, time-varying transient inefficiency, time-invariant airline's unobserved heterogeneity, and random shocks. This model is compared with a nested model, defined by Greene (2005a,b) as a true random effect model, in order to appreciate the additional insights regarding the evaluation of technical efficiency obtained when unobserved heterogeneity is not confounded with time-invariant persistent inefficiency. To the best of our knowledge, this is the first paper that investigates African airline technical efficiency using the four random component stochastic frontier model. From the estimated production frontier each airline's efficiency scores are computed, separated between persistent and transient efficiency, and analyzed according to some possible determinants of efficiency levels.

Based on this advanced model we obtain some interesting results. First, as in Barros and Wanke (2015), we find that public ownership is a factor improving both persistent and transient efficiency. This relation is different in studies regarding non-African airlines (e.g., Yu et al. (2019)), it may be due to protectionism (see Barros and Wanke (2015)), and it opens a relevant ground for policy intervention, leading to increasing the presence of private capitals in African airlines. Second, we find that country's political stability leads to higher transient efficiency but to lower persistent efficiency. This result is interesting because persistent efficiency is usually linked to the optimal use of durable inputs, difficult to adjust in the short run. On the contrary,

[10] In the case of 2 inputs the direct and Allen elasticity of substitution are equal.

[11] In the two inputs case the direct elasticity of substitution coincides with the Allen elasticity of substitution.

better countries' institutions seem to put pressure on airlines towards improvements in technical performances over time. Third, Mediterranean countries have more efficient airlines and this finding is reasonably due to both open sky agreements with Europe (e.g., Morocco), and more intense competition coming from major European airlines. Fourth, we find that the output elasticity of capital (i.e., total seats available in the airline fleet) is higher than that of labor (+0.51% versus 0.07%). This, combined with evidence that the marginal product of capital is always positive for all observations in our data set, confirms the importance of the optimal use of durable capital inputs for African airlines. Last, we find evidence of decreasing returns to scale and an average persistent efficiency equal to 78% and a mean of transient efficiency of 80%. This combined evidence implies that efficiency in African airlines is low and that it is important to implement policies to increase it.

Our results provide an empirical base, obtained with advanced econometric methods, for improving the liberalization of air transportation in Africa. The process to liberalize the market in the continent has been slow so far, and this has led to inefficiency, protectionism, and a gap in the development of low-cost carriers, a business model that in North America, Asia, and Europe has improved competition, reduced prices, increased connectivity and pushed the sector towards a more efficient use of inputs. The full implementation of SAATM (and YD) has to be achieved as soon as possible and more open sky agreements have to be signed, especially with Europe.

There are some possible extensions to the analysis performed in this paper: increase the number of African airlines, increase both the output and the input variables, explore other possible determinants of efficiency, and compare African and non-African airlines. They are left for future research.

References

ADBG (2019). Framework and guidelines to support the aviation sector.

Adom, P. K., Amakye, K., Abrokwa, K. K., and Quaidoo, C. (2018). Estimate of transient and persistent energy efficiency in africa: A stochastic frontier approach. *Energy conversion and management*, 166:556–568.

AFRAA (2020). Afraa 2020 africa air transport report.

Alam, I. M. S. and Sickles, R. C. (1998). The relationship between stock market returns and technical efficiency innovations: evidence from the us airline industry. *Journal of Productivity Analysis*, 9(1):35–51.

Aydın, U., Karadayi, M. A., and Ülengin, F. (2020). How efficient airways act as role models and in what dimensions? a superefficiency dea model enhanced by social network analysis. *Journal of Air Transport Management*, 82:101725.

Barros, C. P. and Wanke, P. (2015). An analysis of african airlines efficiency with two-stage topsis and neural networks. *Journal of Air Transport Management*, 44:90–102.

Barros, C. P. and Wanke, P. (2016). Ground and network efficiency drivers in african airlines: A two-stage network dea approach. In *Airline Efficiency*. Emerald Group Publishing Limited.

Bernardo, V. and Fageda, X. (2017). The effects of the morocco-european union open skies agreement: A difference-in-differences analysis. *Transportation Research Part E: Logistics and Transportation Review*, 98:24–41.

Blonigen, B. A. and Cristea, A. D. (2012). Airports and urban growth: Evidence from a quasi-natural policy experiment (no. w18278).

Button, K. (2002). Airline network economics. *Handbook of airline economics*, pages 27–33.

Button, K., Brugnoli, A., Martini, G., and Scotti, D. (2015). Connecting african urban areas: airline networks and intra-sub-saharan trade. *Journal of Transport Geography*, 42:84–89.

Button, K., Martini, G., and Scotti, D. (2017). *The Economics and Political Economy of African Air Transport*. Routledge.

Button, K., Porta, F., and Scotti, D. (2022). The role of strategic airline alliances in africa. *Journal of Transport Economics and Policy (JTEP)*, 56(2):272–294.

Ciliberto, F., Cook, E. E., and Williams, J. W. (2019). Network structure and consolidation in the us airline industry, 1990–2015. *Review of Industrial Organization*, 54(1):3–36.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., and Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. springer science & business media.

Colombi, R., Kumbhakar, S. C., Martini, G., and Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis*, 42(2):123–136.

Colombi, R., Martini, G., and Vittadini, G. (2017). Determinants of transient and persistent hospital efficiency: The case of italy. *Health economics*, 26:5–22.

Cook, G. N. and Goodwin, J. (2008). Airline networks: A comparison of hub-and-spoke and point-to-point systems. *Journal of Aviation/Aerospace Education & Research*, 17(2):1.

Fageda, X. (2017). International air travel and fdi flows: Evidence from barcelona. *Journal of Regional Science*, 57(5):858–883.

Filippini, M. and Greene, W. (2016). Persistent and transient productive inefficiency: a maximum simulated likelihood approach. *Journal of Productivity Analysis*, 45(2):187–196.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., and Shleifer, A. (1992). Growth in cities. *Journal of political economy*, 100(6):1126–1152.

Good, D. H., Nadiri, M. I., Röller, L.-H., and Sickles, R. C. (1993). Efficiency and productivity growth comparisons of european and us air carriers: a first look at the data. *Journal of Productivity analysis*, 4(1):115–125.

Good, D. H., Röller, L.-H., and Sickles, R. C. (1995). Airline efficiency differences between europe and the us: implications for the pace of ec integration and domestic regulation. *European journal of operational research*, 80(3):508–518.

Graham, A. and Dobruszkes, F. (2019). *Air Transport–A Tourism Perspective*. Elsevier.

Green, R. K. (2007). Airports and economic development. *Real estate economics*, 35(1):91–112.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of productivity analysis*, 23(1):7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of econometrics*, 126(2):269–303.

Heshmati, A. and Kim, J. (2016). Survey of studies on airlines and their efficiencies. *Efficiency and competitiveness of international airlines*, pages 15–50.

Heshmati, A., Kumbhakar, S. C., and Kim, J. (2018). Persistent and transient efficiency of international airlines. *European Journal of Transport and Infrastructure Research*, 18(2).

IATA (2021). Economic performance of the airline industry - 2021. Technical report, IATA.

InterVISTAS (2021). A continental outlook of the benefits of single african air transport market (saatm). Technical report, InterVISTAS.

Lubbe, B. and Shornikova, S. (2017). The development of african air transport. In *The Economics and Political Economy of African Air Transport*, pages 16–39. Routledge.

Manello, A., Scotti, D., and Volta, N. (2022). Air connection dropouts and isolation risks across european regions. *Regional Studies*, 56(3):447–458.

Merkert, R. and Hensher, D. A. (2011). The impact of strategic management and fleet planning on airline efficiency–a random effects tobit model based on dea efficiency scores. *Transportation Research Part A: Policy and Practice*, 45(7):686–695.

Mhlanga, O. (2019). Factors impacting airline efficiency in southern africa: A data envelopment analysis. *GeoJournal*, 84(3):759–770.

Mhlanga, O. (2020). Drivers of efficiency and their influence on airline performances in south africa: a bootstrapped meta-frontier approach. *International Journal of Culture, Tourism and Hospitality Research*.

Mhlanga, O., Steyn, J., and Spencer, J. (2018). The airline industry in south africa: drivers of operational efficiency and impacts. *Tourism Review*.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, pages 69–85.

Njoya, E. T. (2016). Africa's single aviation market: The progress so far. *Journal of Transport Geography*, 50:4–11.

Oum, T. H. and Yu, C. (1995). A productivity comparison of the world's major airlines. *Journal of Air Transport Management*, 2(3-4):181–195.

Oum, T. H. and Yu, C. (1998). Cost competitiveness of major airlines: an international comparison. *Transportation Research Part A: Policy and Practice*, 32(6):407–422.

Oum, T. H. and Yu, C. (2012). *Winning airlines: Productivity and cost competitiveness of the world's major airlines*. Springer Science & Business Media.

Oum, T. H. and Zhang, Y. (1991). Utilisation of quasi-fixed inputs and estimation of cost functions: An application to airline costs. *Journal of transport economics and policy*, pages 121–134.

Pitt, M. M. and Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the indonesian weaving industry. *Journal of development economics*, 9(1):43–64.

Rosenthal, S. S. and Strange, W. C. (2001). The determinants of agglomeration. *Journal of urban economics*, 50(2):191–229.

Roucolle, C., Seregina, T., and Urdanoz, M. (2020). Measuring the development of airline networks: Comprehensive indicators. *Transportation Research Part A: Policy and Practice*, 133:303–324.

Scotti, D., Martini, G., Leidi, S., and Button, K. J. (2017). The african air transport network. In *The Economics and Political Economy of African Air Transport*, pages 40–60. Routledge.

Scotti, D. and Volta, N. (2017). Profitability change in the global airline industry. *Transportation Research Part E: Logistics and Transportation Review*, 102:1–12.

Sickles, R. C., Good, D. H., and Getachew, L. (2002). Specification of distance functions using semi-and nonparametric methods with an application to the dynamic performance of eastern and western european air carriers. *Journal of Productivity Analysis*, 17(1):133–155.

Thomas, D. (2020). Pandemic offers chance to rethink future of airlines. *African business*.

UNECA (2020). Policy research paper covid-19 and african airlines :overcoming a liquidity crisis.

Windle, R. J. (1991). The world's airlines: a cost and productivity comparison. *Journal of Transport Economics and Policy*, pages 31–49.

Yu, C. (2016). Airline productivity and efficiency: concept, measurement, and applications. In *Airline Efficiency*. Emerald Group Publishing Limited.

Yu, H., Zhang, Y., Zhang, A., Wang, K., and Cui, Q. (2019). A comparative study of airline efficiency in china and india: A dynamic network dea approach. *Research in Transportation Economics*, 76:100746.