Research Article

Aviation-caused CO_2 emissions reduction efficiency in EU-28 under CORSIA compliance

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Abstract: The CORSIA is an emission reduction program which is implemented by ICAO for the global air-line industry. The program aims to contribute to the implemented measures to reduce CO_2 emissions from the international aviation network. In this regard, we aim to find out the significant factors that affect the levels of CO_2 emissions in aviation and the most efficient countries in re-ducing them. Firstly, we examine 28-member countries of the EU (European Union) by using the panel data based stochastic frontier analysis and Malmquist productivity indices. The results show that the determinants affecting the emissions caused by aviation statistically significant for the pe-riod 2008-2017: Energy consumption per flight; millions of passenger-kilometers, freight and mail million tonne-kilometer; the number of commercial aircraft fleets by age groups; the number of countries' airports; and globalization index of the related country. Moreover, efficiency scores which are obtained by stochastic frontier analysis and Malmquist productivity index differ among the countries. Eastern European countries are observed to be superior in terms of technical effi-ciency. However, there is no significant increasing or decreasing trend in technical efficiency for EU 28 countries. This result is an indication that CORSIA's emission reduction expectations will not be realized quickly, especially when considering the extensive use of aviation in the globalized countries.

Keywords: CORSIA, CO_2 emissions, aviation, efficiency

CORSIA uyumluluğu kapsamında AB-28'de havacılık kaynaklı CO_2 emisyonlarını azaltma verimliliği

Özet: CORSIA, ICAO tarafından küresel havayolu endüstrisi için uygulanan bir emisyon azaltma programıdır. Program, uluslararası hava taşımacılığı ağından kaynaklanan CO_2 emisyonunu azaltmak için uygulanan önleyici faaliyetlere katkıda bulunmayı amaçlamaktadır. Bu kapsamda çalışmamız hava taşımacılığındaki CO_2 emisyon düzeylerini etkileyen önemli faktörleri ve emisyonun azaltılmasında en etkin olan ülkeleri ortaya çıkarmayı amaçlamaktadır. İlk olarak, panel veri tabanlı stokastik sınır analizi ve Malmquist verimlilik endeksi yaklaşımlarını kullanarak AB üyesi olan 28 ülkenin analizi yapılmaktadır. Sonuçlar, havacılık kaynaklı emisyonların belirleyicilerinin 2008-2017 dönemi için; uçuş başına enerji tüketimi; taşınan milyon yolcu/kilometre, taşınan milyon ton yük ve posta ton/kilometre; yaş gruplarına göre ticari uçak filosu sayısı; ülkelerin havaalanlarının sayısı; ve ilgili ülkenin küreselleşme endeksi olduğunu göstermiştir. Ayrıca stokastik sınır analizi ve Malmquist verimlilik endeksi ile elde edilen etkinlik puanları ülkeler arasında farklılık göstermektedir. Doğu Avrupa ülkelerinin teknik verimlilik açısından daha üstün olduğu görülmektedir. Ancak, AB 28 ülkeleri için teknik verimlilikte önemli bir artış veya azalış eğilimi yoktur. Bu sonuç, özellikle küreselleşmiş ülkelerde havacılığın yaygın kullanımı düşünüldüğünde CORSIA'nın emisyon azaltım beklentilerinin hızlı bir şekilde gerçekleştirelemeyeceğinin bir göstergesi olabilir.

Anahtar Kelimeler: CORSIA, CO_2 emisyonları, hava ulaşımı, etkinlik

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1. Introduction

The relation between energy and climate change is undoubtedly one of the most crucial topics debated both globally and nationally. There lie the energy efficiency and energy-saving issues at the heart of it, not that because energy is a huge burden as a private cost on businesses alone, but also because it has been generating a chaotic by-product and social cost called climate change, a negative externality that even future generations will be paying. While entering the renewable era challenges the climate change drift, it is not solely sufficient to stop or mitigate it on its own. Managing how to optimize the utilization of energy as a complementary instrument would save energy by generating efficient use. To struggle against global warming and environmental problems, EU member states are requested to set their energy savings by 9 % between 2008 and 2016 and to target their energy efficiency at 20 % until 2020 by following the "Energy Efficiency Action Plan" (EC, 2013). In addition, according to the directive in 2018 (EU, 2020), it has a view that it should be reduced by 32.5 % by 2030.

Tracking Transport Report (2019) of IEA (International Energy Agency) claims that transportation is still responsible for one-fourth of direct CO_2 emissions. Global transport emissions increased by only 0.6 % in 2018 –much less than the average 1.6 % of the last decade- due to efficiency improvements, electrification, and biofuels. While road vehicles account for nearly three-quarters of this, emissions from shipping and aviation continue to rise. This paper focuses on the latter.

According to the European Commission, "Someone flying from London to New York and back generates roughly the same level of emissions as the average person in the EU does by heating their home for a whole year" (EC, 2020). The share of aviation in the total transport sector greenhouse emissions is around 4 to 6 %, and the air transportation is responsible for approximately 2 to 4 % off all the anthropogenic carbon emissions in 2010 (Wise et al., 2017). Another report notes that the aviation sector has a 2.6 % share in global carbon dioxide emissions and about 3.5 % of total anthropogenic carbon emissions (Staples et al., 2018; ICAO, 2016). IPCC (1999) indicates that the CO_2 emissions generated by aviation are responsible for about 2.5 % of global greenhouse gas emissions, but the share is expected to rise to 10 %. The demand for the aviation sector is growing gradually, and the number of commercial aircraft is expected to double by 2035 (Hassan et al., 2018). The common argument in the studies, as mentioned above, is that the relative share of the aviation sector in the global carbon dioxide emissions will grow in the not too distant future. Contrarily, there are also promising attempts in the air. The world's first fully-electric commercial aircraft has taken its test flight, taking off from the Canadian city of Vancouver and flying for 15 minutes (Guardian, 2020).

The CORSIA (Carbon Offsetting and Reduction Scheme for International Aviation), adopted in October 2016, is an emission reduction approach for the global airline industry developed by the International Civil Aviation Organization (ICAO). Aircraft operators who operate international flights in all ICAO Member States are obliged to monitor, report and verify CO_2 emissions from their flights from 2019, regardless of their participation in the CORSIA program. Apart from this, they are also required to comply with Offset Requirements every three years (starting from 2021) by the CORSIA. The implementation of the CORSIA Program consists of 4 stages: Basic period: 2019-2020, Pilot stage: 2021-2023 (voluntary), First stage: 2024-2026 (voluntary), and Second stage: 2027-2035. Given the emission reality, the International Air Transport Association (IATA) sets a goal to reduce CO_2 emissions of 50 % by 2050 (IATA, 2017). It aims to ensure that any rise in international aviation emissions above the 2020 level is offset elsewhere (Aircarbon, 2020). On the other hand, the energy efficiency obligation scheme, which is linked to Directive 2012/27/EU, requires each member state to implement an energy efficiency obligation scheme to decrease a substantial amount of energy consumption over the 2014-2020 obligation period (ENSPOL, 2015).

The literature shows that the studies about the emissions in the aviation sector are generally conducted by using the data of the airline companies (e.g., Arjomandi et al., 2018; Brueckner and Abreu, 2017; Wilkerson¬ et al., 2010). However, if the targets of the EU countries are analyzed, more accurate results seem to be obtained by examining the CO_2 emissions caused by both domestic and international aviation industry based on countries, rather than airline companies, especially with regard to CORSIA. Besides, conducting an efficiency analysis will show the role model and guide the targets of countries. This, we believe, is one of the critical contributions of the present study.

This work aims to determine the sources of aviation-caused CO_2 emissions in EU member countries. We attempt to find solutions to the following two problems. First, we find relatively efficient countries. Second, we explore the criteria that are necessary for countries to mitigate CO_2 emissions.

The flow of the paper is as follows. The next section provides the literature review on the issue under study. Section 3 defines the methodology in detail, along with the presentation of some statistics and figures. In Section 4, we present the results of our investigation and then proceed with the discussions of the results in Section 5. Finally, in the last section, we conclude.

2. Literature review

To the best of our knowledge, the literature on aviation emissions and efficiency has mostly focused on airline firms rather than the countries regarding aviation that led to CO_2 emissions. For instance, Meleo et al. (2016) estimate the impact of the cost of the European Union Emission Trading Scheme (EU-ETS) on the Italian aviation sector. The results show that there is still a limited effect of the scheme on the airline companies and society. Wilkerson et al. (2010) analyze the emission of global commercial airlines by using the data between 2004 and 2006. They conclude that although the flight variable consists of 85% short-haul flights, they produce only 39.7 % of CO_2 emissions.

Li et al. (2016) evaluate the airline efficiency concerning the EU-ETS on three grounds: Operations Stage, Services Stage, and Sales Stage. To analyze the efficiency of 22 international airlines between 2008 and 2012, they established two models: Network Slack – Based Measure with weak disposability and Network Slack – Based Measure with strong disposability. Their model uses Green Gas Emissions as an undesirable output. They find that the average efficiency of European airlines is much higher than that of non-European airlines. Pan et al. (2014) introduce three mitigation methods and compare these methods with others to solve the aviation CO_2 emissions problem. They also analyze the feasibility of these three methods by using the historical data of the aviation sector and the AHP method. Based on the results of their evaluation, they propose a dynamic mitigating method to reduce aviation emission. Besides these articles, in Table 1, we list some studies investigating CO_2 emission or greenhouse gasses in the airline sector by indicating their methods and variables. Our study is different from these studies in a way that, while they use airline companies as an observation unit, we use countries. This is important because CORSIA is not based and focused on airlines companies. Countries are also responsible for the emission-causing flight in their own airspace. Therefore, the success of countries, that is, their effectiveness in reducing CO_2, should be examined.

Some studies aim to examine the effects of the energy obligations scheme of the European Union. For example, to understand the public perception towards emission policy options (such as fiscal policies – e.g., tax, etc.- on individuals using aviation services), In Kantenbacher et al. (2018), in which 2066 British adults were questioned, found out that public prefers the fiscal burden to be incurred by the aviation industry rather than policies levied on an individual level. Zhou et al. (2016) also carry out a scenario analysis that shows that the jet fuel substitute, fuel intensity, and traffic demand -being the most important one- emerged as the critical factors of China’s civil aviation CO_2 emissions. The results pointed out the need for the implementation of more policies, including a carbon tax on jet fuel and R&D support to promote fuel efficiency. Gonzalez and Hosoda (2016), on the other hand, investigated the effect of the aircraft CO_2 emission and aviation fuel tax on the environment by using Bayesian structural monthly time series for Japan for the period 2004-2013. They concluded that the fuel tax leads to a reduction in the amount of CO_2 emissions. Also, FitzGerald and Tol (2007) set up a simulation model of international tourist flows to estimate the effect of CO_2 emissions caused by the fuels of aviation in the ETS. They claim that the number of tourists in Europe will fall by up to 0.6 % when ETS permits are given, whereas the number in the rest of the world will increase. Hence, they indicate that permits may have almost no effect on reducing CO_2 emission and might have a negative impact on the economy.

Table 1. A series of studies on greenhouse gasses in the airline sector

Author	Scope	Model	Dependent Variables or Outputs	Independent Variables or Inputs
Scotti and Volta (2015)	18 Global Airlines	Biennal Malmquist–Luenberger productivity index	RPK, Total freight tonne-kilometers (TFTK), CO_2 (Undesirable Output)	ASK, ATK
Cui et al. (2016)	18 Global Airlines	Dynamic Environmental DEA	Total Revenue, Greenhouse Gas Emission	Number of Employees, Aviation Kerosene,
Li et al. (2016)	22 Global Airlines	Network Slacks-Based Measure	Total Business Income, Greenhouse Gasses Emission, ATK (Intermediate Products), RTK (Intermediate Products), Available Seat Kilometers (ASK) (Intermediate Products), Revenue Passenger Kilometers (RPK) (Intermediate Products)	Number of Employees, Aviation Kerosene, Fleet Size, Sales Cost
Brueckner and Abreu (2017)	16 US Airlines	Regression	Total Fuel Usage	Available Tonne Miles (ATM), Average Seat Capacity, Average Stage Length, Average Load Factor (Average LF), Average Vintage of Aircrafts, Percentage of Flight Delay, Average Annual Fuel Price
Liu et al. (2017)	12 Chinese Airlines	Global Malmquist carbon emission performance index (GMCPI) Bootstrapping GMCPI	Revenue Tonne Kilometers (RTK), CO_2 (Undesirable Outputs)	Capital, Labor
Li and Cui (2017)	29 Global Airlines	Network Range Adjusted Environmental DEA	ASK, RPK, Total Revenue Greenhouse Gasses Emissions, ASK (Intermediate Products), RPK (Intermediate Products),	Operating Expense, ASK, Fleet Size, RPK, Sales Costs

Table 1. A series of studies on greenhouse gasses in the airline sector (cont'd)

Author	Scope	Model	Dependent Variables or Outputs	Independent Variables or Inputs
Zhang et al. (2017)	7 Chinese Airlines and 10 US Airlines	Slacks-based measurement (SBM) Malmquist-Luenberger index Tobit Regression Model	RTK, Operating Revenue, CO_2	Aircraft, Labor, Fuel
Chen et al. (2017)	12 Chinese Airlines	Stochastic Network DEA (SNDEA)	Cargo, Number of Passengers Number of Landings and Take-offs (Intermediate Products), Delays (Undesirable Outputs), CO_2 (Undesirable Outputs),	Fuel, Number of Planes, Number of Employees
Li and Cui (2018)	28 Global Airlines	DEA cross pollution abatement costs (PAC)	Total Revenue Greenhouse Gasses Emissions	Number of Employees, Fleet Size, Energy (Aviation Kerosene),
Arjomandi et al. (2018)	7 European and 22 Asian Airlines	Meta – Frontier DEA	Available Tonne Kilometers (ATK), CO_2 (Undesirable Output)	Number of Employees, Capital

Besides these, some studies have tried to identify the variables which might have a tied in emissions or efficiency. Rizet et al. (2012), for instance, analyze the relationship between vehicle load, CO_2 emissions, and energy efficiency and observe that an increase in the load factor leads directly to an increase in the road efficiency. Andreoni and Galmarini (2012) performed a decomposition analysis to find the main reasons behind CO_2 emissions of European transportation for the period 2001-2008. The results suggest that economic growth is the main reason for the increasing CO_2 emissions caused by both water and aviation transport activities in EU-27. Dynamic demand management is also seen as an alternative tool for reducing aviation CO_2 emissions. To assess this, Molloy et al. (2012) establish a regression model that will help determine the European air travel demand elasticities. Service frequencies were found to be more efficient in reducing aviation-related CO_2 emissions. An increase in the level of service frequency can cause a reduction in passenger demand, though this may negatively affect the economy.

According to energy obligations schemes amongst European countries, ambitious targets are set to reduce energy densities and to achieve energy efficiency policies. One of the essential instruments of energy efficiency policies is the “White Certificates System”, which has been implemented in some European countries so far. Based on this system, obliged participants have to achieve energy efficiency targets. Market participants who do not fulfil these obligations either get a penalty or receive a White Certificate (Düzgün, 2014). A white certificate could be a tradable resource which proofs that a certain rate of energy-saving funds has been accomplished relative to a standard. To the best of our knowledge, France and Italy comply with these obligations for the transportation sector. Since January 1st, 2012, the EU-ETS has also included aviation emissions. Also, in 2016, ICAO (International Civil Aviation Organization) agreed on the CORSIA, which intends to arrange CO_2 emission levels by requiring airlines to offset the growth of their emission levels following 2020. Airlines are already asked to show emission values on all routes since January 2019, and they are free to take some actions to balance emissions by buying appropriate amounts of emissions from other sectors (e.g., renewable energy). All countries in the EU will join the scheme from the start (EC, 2020).

As it stands, the emission studies originating from the aviation sector have approached the issue through airline companies. However, when the EC targets are examined in terms of EU countries, we expect that we will reach more accurate results. For this purpose, we will analyze some factors that reduce the emissions in the aviation sector in terms of CORSIA and examine the efficiencies of successful EU-28 countries. The efficiency analysis will guide the targets of countries through effective factors in aviation. In doing so, the study expects to make important contributions to the field.

3. Methodology

In this study, we use two methodologies. These are panel data based stochastic frontier analysis and Malmquist productivity index to provide robustness check between efficiency scores. Since our data set is a balanced panel data set that includes both time and cross-sections; and since there is only one dependent variable (CO_2 emissions in aviation) but more than one factor that can affect CO_2 emissions in aviation in the data set, it is convenient to apply panel data models. Thus, firstly we estimate the stochastic frontier analysis as a parametric method to select variables which have a significant effect on CO_2 emissions in aviation and obtain efficiency scores. Then, we apply Data Envelopment Analysis (DEA) as a nonparametric method to calculate the efficiencies of countries in reducing CO_2 emissions in aviation by using the statistically significant variables which are obtained in the stochastic frontier analysis. Last but not least, we use the Malmquist productivity index, which is based on DEA. The reason is two-fold. The first one is because we want to examine the temporal changes in the activities of countries. The second one is to compare these changes in factors affecting the reduction of CO_2 emission efficiency. This is because of having time and cross-section dimensions in our data set. Finally, we aim to compare the results of these methods with each other.

3.1. Stochastic frontier analysis

Stochastic Frontier Analysis (SFA) is a parametric method used in measuring relative efficiency scores. It divides the error term in the function into random error and ineffectiveness. Thanks to ineffectiveness term, the relative technical efficiency scores of decision-making units are obtained. The method uses a cost function as a boundary so that firms can be compared and inefficiency can be measured using the existing data set. Following Sarafidis (2002), the mathematical representation of the function is as follow:

$$C_i = f(y_i, \beta) + w_i; \qquad w_i = v_i + u_i \tag{1}$$

In Equation 1, the cost limit function is shown as $f(y_i, \beta)$ and w_i is represented by the sum of the term representing technical inefficiency (u) and the random error term (v) of the regression. Since there cannot be an inefficiency term lower than the cost limit, the inefficiency error term cannot have a negative value, while the random error term can take both negative and positive values (Kumbhakar and Lovell, 2000).

If one wants to calculate the technical efficiency value for any DMU in the data set, equation 2 should be used:

$$TE_i = C_i / f(x_i, \beta) \tag{2}$$

If the decision-making unit is producing at the maximum possible output amount, that is, at the border, TE = 1, otherwise the technical efficiency score will be less than “1” (Chakraborty et al. 1999).

SFA presents statistically significant variables on the dependent variable, unlike the data envelopment analysis and Malmquist productivity index. The representation of the model in the panel data is as follow in equation 3 (Kumbhakar and Lovell, 2000).

$$y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + v_{it} - u_{it} \tag{3}$$

where

$$u_{it} = \exp(-\eta(\mathrm{t} - \mathrm{T}_i))u_i \tag{4}$$

Here y shows the dependent variable, i shows cross-sectional units, t shows time. β_0 is constant, β_j is the vector of slope parameters. x_j represents the independent variables. T_i is the last period in the ith panel, η is the decay parameter, $u_i \sim N^+(\mu, \sigma_u^2)$ denotes the truncated-normal distribution, $v_{it} \sim N(0, \sigma_v^2)$ denotes normal distribution, and u_i and v_{it} are distributed independently of each other and the covariates in the model. (Kumbhakar and Lovell, 2000).

3.2. Data envelopment analysis (DEA) and Malmquist productivity index

We use the DEA (data envelopment analysis), which is a nonparametric method, because of being part of the Malmquist productivity index. DEA is easily measurable with the relative efficiency of the decision units measured by the inputs and outputs measured at multiple and different scales. By measuring the efficiency of each of the decision units examined with DEA, the decision-making unit with the lowest efficiency is determined, and data are obtained about the extent to which their efficiencies can be increased.

The DEA method can be used for both input-oriented and output-oriented. For the most efficient input composition, DEA models for input can be used to produce a specific output composition. The DEA models for output studies how much output composition can be achieved with a particular input composition (Kula et al. (2009).

The DEA model is introduced in 1978 by Charnes et al. The model can find how to measure the efficiency in Linear Programming (LP) model. Each input and outputs have their weights, and DEA does the formulation of choice of the weights. There are two kinds of CCR (Charnes, Cooper, Rhodes) models which are input-oriented and output-oriented. In the CCR model, the Constant Return to Scale (CRS) approach is used (Charnes et al., 1978).

Another DEA model, called BCC (Banker, Charnes, and Cooper) that is introduced by Banker et al. (1984) uses Variable Return to Scale (VRS) approach, which points out that increasing 1 unit of input does not lead to 1 unit of output increase. However, in the CRS approach, increasing 1 unit of input leads to 1 unit of increase in output. In case, there are n number of DMUs (Decision Making Unit), (DMU_j: $j = 1, 2, \ldots ,n$) which require m number of inputs (x_i:$i = 1, 2, \ldots,m$) to produce s number of outputs (y_r: $r = 1, 2, \ldots ,s$), the output-oriented (BCC-O) model evaluates the efficiency of DMU_0.

By solving the linear program, as shown below:

$$min \sum_{i=1}^{m} v_i X_{ik} - v_k$$
$$s.t. \sum_{r=1}^{s} u_r Y_{rk} = 1$$
$$\sum_{r=1}^{s} u_r Y_{rj} + \sum_{i=1}^{m} v_i X_{ik} - v_k$$
$$v_k, \text{ free}$$
$$v_i \geq \varepsilon, \; i = 1,2,\ldots,m$$
$$u_r \geq \varepsilon, \; r = 1,2,\ldots,s \qquad (5)$$

In Equation 5, x represents the inputs with v_i weights, and y represents the outputs with u_r weights of the jth DMU, and all inputs and outputs are nonnegative. Also, ε is non-Archimedean little value for forestalling weights to be equal to zero (Toloo et al., 2009). With this formulation, DEA finds the relative efficiency of the DMUs, but, the method only distinguishes efficient and inefficient DMU's.

In DEA, the technical efficiency values of the decision units are calculated for each period. It consists of pure technical efficiency and scale efficiency and is obtained by multiplying these two indices. The pure technical efficiency and efficiency of the scale indicate the success of the company in producing the appropriate scale (Kula et al., 2009).

Caves et al. (1982) developed a DEA-based technique to measure the TFP index. The Malmquist total factor productivity (TFP) index measures the change in total factor productivity between two data points by calculating the ratio of the differences of each data point according to the current technology. It can be decomposed into changes in efficiency and technology. The distance function is used for this measurement (Kula et al., 2009). The distance function based on output can be shown with S possible set of y to be generated by x as follows: $D_0^s(x, y)$. If the vector of y is above the S (production limit), D equals to "1"; if the vector of y defines a non-active point in S, then D will be bigger than "1"; and if y identifies a point that is not possible outside S, then D is smaller than "1". Malmquist TFP change index based on output between t period and subsequent $t + 1$ period can be calculated as follows:

$$M_0(x^t, y^t, xt^{+1}, y^{t+1}) = sqrt\ ((D_0^t\ (x^{t+1}, y^{t+1}) / (\ D_0^t(x^t, y^t)) * (D_0^{t+1}\ (x^{t+1}, y^{t+1}) / (\ D_0^{t+1}\ (x^t, y^t))) \qquad (6)$$

In equation 6, $D_0^t(x, y)$ denotes the technological change from period t to period $t + 1$. When the value of M_0 function is higher than "1", there is a growth in TFP from t period to $t + 1$ period. When it is less than "1", there is a decrease in TFP considering the same periods. This equation can also be expressed as follows:

$$M_0(x^t, y^t, xt^{+1}, y^{t+1}) = (D_0^{t+1}\ (x^{t+1}, y^{t+1}) / D_0^t(x^t, y^t)) * sqrt\ ((D_0^t\ (x^{t+1}, y^{t+1}) / D_0^{t+1}\ (x^{t+1}, y^{t+1}))* (D_0^t\ (x^t, y^t)) / (D_0^{t+1}\ (x^t, y^t))) \qquad (7)$$

In the above equation, the ratio outside the square root is the measure of the change of technical efficiency between period t and period $t + 1$. The expression in the square root describes the change in technology. Here, the change in the technical efficiency gives an assessment of the approaching process of the decision units to the effective boundary, while the change in the technology changes the active boundary over time (Kula et al., 2009).

Using the above methodologies, we will find the factors affecting aviation-led CO_2 emissions as well as the countries that are efficient in reducing CO_2 emissions based on CORSIA criteria by using the data for EU-28 countries, which are drawn from Eurostat air transport statistic database for the 2008-2017[*] period.

[*] Data for EU-28 countries are available after 2008. That is, after Romania and Bulgaria joined the EU in 2007.

4. Data

Our panel data set, consisting of 10-year aviation statistics of EU-28 countries, is balanced. In our models, the inverse value of the amount of CO_2 Emissions in aviation (Millions tonne) is used as output since the main goal is the reduction in CO_2 Emissions (see Lewis and Sexton, 2004). Before establishing the regression model, we examine the correlation matrix and find that the energy in aviation (millions of tonnes of oil equivalent) is highly correlated with other independent variables. Dividing the energy variable by the total number of flights, we reduce the VIF and block the multicollinearity. We also use "millions of passenger-kilometers", "freight and mail million tonne-kilometer", "total commercial aircraft fleet by ages" (less than 5 years, 5-9 years, 10-14 years, and 15-19 years), "the total number of airports" most of which are also used in the literature (see, Table 1), and "globalization index" (which is proposed by Dreher, 2006) as inputs or explanatory variables. The Globalization Index is an index representing the degree of globalization of 122 countries which covers political, social and economic globalization components. Through globalization, industries achieve productivity. The rapid development of the aviation industry is driven by this growth, as more people fly and more goods are transported (Henningsen, 2010). Considering the link between aviation and globalization, it is an important factor in aviation-related modelling. Moreover, the fact that the fleets owned by the airlines, which use the country as a base, are young enables the use of energy-efficient fuels. Therefore, the fleet age is also an important variable (Merkert and Hensher, 2011; Grote et al., 2014).

These variables are also selected after applying the Stepwise[†] method. The variance inflation factor (VIF) of the last model is obtained as lower than 10. We also take the logarithm of variables to prevent heteroscedasticity problem. The detailed descriptive statistics of variables are shown in Table 2 for the 280 (from 28 * 10) observations. It is observed that the standard deviations of all statistics are found higher than the mean values of variables. That is, the variabilities of the factors are quite high.

Table 2. Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
CO_2 in Aviation (Millions tonne)	5.5	8.9	0.1	37.5
Energy in Aviation (Millions of tonnes of oil equivalent)	1.8	3.0	0.0	12.8
Millions of passenger-kilometers	27004.9	36541.0	175.0	189534.0
Freight and mail Million tonne-kilometer	520.1	619.8	1.0	3375.0
Total Commercial aircraft fleet Less than 5 years	62.4	89.9	0.0	451.0
Total Commercial aircraft fleet 5-9 years	60.6	80.8	0.0	375.0
Total Commercial aircraft fleet 10-14 years	41.9	58.4	0.0	258.0
Total Commercial aircraft fleet 15-19 years	31.6	44.8	0.0	253.0
Total Number of Airports	14.6	16.5	1.0	66.0
Globalization Index	83.6	4.3	72.4	91.3

We estimate panel-based stochastic frontier analysis which is shown in equation 8 by using Stata 14 software.

$$\ln(1/CO_2 \text{ in Aviation})_{it} = \beta_0 + \beta_1 \ln(\text{Energy in Aviation per Flight})_{it} + \beta_2 \ln(\text{Millions of passenger-kilometers})_{it} + \beta_3 \ln(\text{Freight and mail Million tonne-kilometer}) + \beta_4 \ln(\text{Total Commercial aircraft fleet Less than 5 years}) + \beta_5 \ln(\text{Total Commercial aircraft fleet 5-9 years}) + \beta_6 \ln(\text{Total Commercial aircraft fleet 10-14 years}) + \beta_7 \ln(\text{Total Commercial aircraft fleet 15-19 years}) + \beta_8 \ln(\text{Total Number of Airports}) + \beta_9 \ln(\text{Globalization Index}) + v_{it} - u_{it} \quad (8)$$

[†] Other variables that are eliminated by Stepwise (such as total aircraft fleet by type; total aircraft fleet by type of number of seats; total flight of freight and mail board, load; total flight of passenger or cargo flight; GDP constant (2010); total air traffic by type of aircraft (passenger, cargo etc.); total number of passengers arrived, total number of passenger departure; population of the country) But we could not find any statistically significant effect.

5. Results

In table 3, we present the results of the panel-based stochastic frontier analysis. Regarding the inverse value of the dependent variable; Energy in Aviation Per Flight, Millions of passenger-kilometers, Freight and mail Million tonne-kilometer, Total Commercial aircraft fleet by ages, Globalization Index and Total Number of Airports are found to have a positive and significant effect on CO_2 emission in aviation. In the model, *sigma2* shows the variance of the error term (w_i), while *lnsigma2* shows its natural logarithm. The variance of the random error term (v_i) is represented by *sigma_v2* and the variance of the technical inefficiency error term (u_i) is represented by *sigma_u2*. Gamma coefficient shows *sigma_u2 / sigma2*. The greater this value, the more of the variance in the error term is explained by the inefficiency term. *Lgtgamma* shows the logit value of the *gamma* coefficient. *Eta (η)* gives information about whether efficiency/inefficiency changes over time (Barros, 2005). In our model, the fact that the *Eta (η)* coefficient is insignificant shows that the efficiencies or inefficiencies of the countries in reducing CO_2 does not change over the years.

Table 3. Results of panel based stochastic frontier analysis

		Number of obs	=	280
		Number of groups	=	28
		Obs per group:		
		min	=	10
		avg	=	10
		max	=	10
		Wald chi2(9)	=	218.24
		Prob > chi2	=	0.00
		Log likelihood	=	161.97
	Coefficient	Standard Error	z	P>z
Ln(Energy in Aviation Per Flight)	-0.54	0.08	-7.12	0.00
Ln(Millions of passenger-kilometers)	-0.24	0.07	-3.32	0.00
Ln(Freight and mail Million tonne-kilometer)	-0.14	0.06	-2.62	0.01
Ln(Total Commercial aircraft fleet Less than 5 years)	-0.06	0.01	-3.98	0.00
Ln(Total Commercial aircraft fleet 5-9 years)	-0.01	0.01	-0.45	0.65
Ln(Total Commercial aircraft fleet 10-14 years)	-0.05	0.01	-3.39	0.00
Ln(Total Commercial aircraft fleet 15-19 years)	-0.07	0.01	-6.53	0.00
Ln(Globalization Index)	-1.55	0.58	-2.67	0.01
Ln(Total Number of Airports)	-0.16	0.04	-4.02	0.00
Constant	5.05	2.86	1.77	0.08
/mu	1.65	0.21	7.73	0.00
/eta	0.00	0.00	0.25	0.81
/lnsigma2	-0.43	0.36	-1.20	0.23
/lgtgamma	4.18	0.38	10.89	0.00
sigma2	0.65	0.23		
gamma	0.98	0.01		
sigma_u2	0.64	0.23		
sigma_v2	0.01	0.00		

The operating income per unit production of money, labor and energy of airlines is increased by more passengers per flight (Caves et al., 1983). As millions of passenger-kilometers and freight and mail million tonne-kilometer increase, the number of flights is expected to increase. This in turn will lead to higher CO_2 emissions. On the other hand, air travel consumes large quantities of energy and releases greenhouse gasses into the atmosphere (Becken, 2002). Since one of the most important variables in causing CO_2 emission in aviation is energy, the increase in the amount of energy consumed per flight is expected result in higher CO_2 emission. Moreover, younger aircraft are expected to be more fuel-efficient than older aircraft. They also contribute less to air pollution and the production of carbon (Zhang et al.,2017). Considering that older aircraft have inefficient fuel consumption, it is expected to increase CO_2 emissions. When the number of fleets owned by countries in the model is examined by age, it is seen that the number of fleets of all ages (even if they are young) contributes positively to CO_2 emissions. In this case, it can be said that as of 2017, in Europe, even the aircraft that are less than 5 years old are not using energy-efficient fuel sufficiently. On the other hand, since the increase in the number of airports will increase the number of runways, it will provide more air traffic. Finally, among the more globalized countries, CO_2 emissions are expected to increase as the number of both commercial and passenger flow is foreseen to be higher (see Henningsen, 2010). The results in our model support all the aforementioned arguments.

Table 4. Efficiency scores from stochastic frontier analysis

	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Austria	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
Belgium	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Bulgaria	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
Cyprus	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.10
Czechia	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
Germany	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Denmark	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Estonia	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51
Greece	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Spain	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Finland	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
France	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Croatia	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
Hungary	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34
Ireland	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Italy	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Lithuania	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.48	0.48
Luxembourg	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Latvia	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
Malta	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Netherlands	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Poland	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23
Portugal	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Romania	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Sweden	0.17	0.17	0.17	0.17	0.18	0.18	0.18	0.18	0.18	0.18
Slovenia	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
Slovakia	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
United Kingdom	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Technical efficiency scores obtained from the panel based stochastic frontier analysis are presented in Table 4. This table indicates the following results: 1) When viewed from the temporal perspective, the average efficiency of reducing CO_2 emission from aviation in Europe is 0.25. This ratio does not differ from year to year as indicated by the *Eta* coefficient. In general, no increase in efficiency has been found in terms of reducing CO_2 emissions in the European region. The results indicate that there is no significant progress in Europe between 2008 and 2017. Considering the growth in the aviation sector, with a 41% increase in the number of passengers carried (World Bank, 2020), this result is straightforward. 2) The low level indicates that there is a relatively large gap between the actual output of the CO_2 utilization and the potential output. There are also about 18 countries below the average value. 3) Slovakia is the country that has achieved the most effective reduction in CO_2 emission with the determined inputs. Although countries such as Slovenia and Estonia have lower average emission values, none of them has been found to be the most efficient country when inputs are considered. 4) In spatial terms, efficiency values differ between countries. Generally, it is seen that eastern European countries are effective in reducing CO_2 emissions.

After this step, we compared the results of DEA and Malmquist productivity indexes, which are nonparametric methods, regarding the results of the stochastic frontier analysis. DEA is one of the most used nonparametric methods that evaluate the relative efficiency of the given units. On the other hand, the Malmquist Productivity Index (MPI) developed by Caves et al. (1982) is used for efficiency in panel data. This method not only evaluates the relative efficiency but also decomposes the efficiency and technological change. In order to obtain reliable results from DEA, we need homogeneity in the values of the variables. Therefore, the variables are standardized by dividing each value with the maximum value of those variables so that we can ensure the homogeneity (see Kao, 2006). Also, since the CO2 emissions are undesired variables, these variables' values are standardized with taking the inverse (see Lewis and Sexton, 2004).

Since we take the inverse of all values of CO_2 emissions, when the values of the variables increase, there is a decrease in the amount of CO_2 emissions. The working principle of the output-oriented model is to increase efficiency by increasing the outputs while the inputs are constant. Since it is aimed to decrease CO_2 emission in aviation (to increase $1/CO_2$), this is the reason to choose the output-oriented DEA for our model (see Tyteca, 1996). Also, we use the variable return to scale model since when there is an increase in inputs, there is not an increase at the same rate in outputs.

The number of DMU should be greater than 3 x (number of inputs + number of outputs) or the number of inputs x number of outputs (Egilmez and Deborah, 2013). Our dataset used for efficiency includes 28 DMU, which is greater than 9, so this means that the dataset is sufficient for this method.

Stata 14 software is used to implement the Malmquist productivity index (MPI) and to summarize the change between 2008 and 2017. Total Factor Productivity Change (Tfpch) or, in other words, MPI, which can be divided into two: (i) Technical Efficiency Change (Effch); (ii) and Technological Change (Techch). The last one is also two-fold: (i) efficiency change due to managerial improvement, i.e., Pure Efficiency Change (Pech); and (ii) efficiency towards improvement, i.e., so-called Scale Efficiency Change (Sech). Both are shown as average in years in Table 5. According to DEA results (given in the appendix as Table A1)[‡], Cyprus, Estonia, Lithuania, Latvia, Malta, Slovenia and Slovakia are relatively more efficient on CO_2 emissions in aviation in all years. We observe that the stochastic frontier analysis provides a better separation. On the other hand, when the efficiency results obtained from DEA and stochastic frontier analysis are compared, it is seen that the magnitude of the spearman rank correlation coefficient varies between 0.72 and 0.78 in years. In this case, there is a sufficiently high degree of correlation / similarity between the results of the two methods.

Table 5. Malmquist productivity index

	Tfpch	**Effch**	**Techch**	**Pech**	**Sech**
Austria	1.00	1.05	0.97	1.05	1.00
Belgium	1.01	1.05	0.97	1.06	1.00
Bulgaria	1.17	1.23	1.14	1.44	1.54
Cyprus	0.52	1.14	0.61	1.00	1.14
Czechia	1.08	1.03	1.06	1.03	1.00
Germany	1.02	1.06	0.97	1.06	1.00
Denmark	1.01	1.05	0.97	1.06	1.00
Estonia	1.64	1.08	1.33	1.00	1.08
Greece	1.13	1.15	1.03	1.17	1.00

[‡] Stata software gives efficiency scores greater than 1. For convenience, the inverse scores (which are between 0 and 1) are calculated and given in this table.

Table 5. Malmquist productivity index (cont'd)

	Tfpch	Effch	Techch	Pech	Sech
Spain	1.02	1.07	0.97	1.07	1.00
Finland	1.02	1.07	0.97	1.06	1.01
France	1.00	1.05	0.97	1.05	1.00
Croatia	0.60	1.21	0.54	1.15	1.11
Hungary	1.53	1.08	1.18	0.92	1.48
Ireland	1.02	1.05	0.97	1.05	1.00
Italy	1.01	1.06	0.97	1.05	1.00
Lithuania	1.01	1.09	0.95	1.00	1.09
Luxembourg	1.08	1.03	1.06	0.90	1.33
Latvia	1.10	1.24	0.96	1.00	1.24
Malta	1.20	1.00	1.20	1.00	1.00
Netherlands	1.01	1.05	0.97	1.05	1.00
Poland	1.07	1.10	0.98	1.11	0.99
Portugal	1.05	1.09	0.97	1.09	1.00
Romania	1.03	1.18	0.89	1.83	1.80
Sweden	0.94	0.99	0.97	1.00	0.99
Slovenia	0.98	1.00	0.98	1.00	1.00
Slovakia	1.07	1.00	1.10	1.00	0.99
United Kingdom	1.01	1.05	0.97	1.05	1.00

Based on the stochastic frontier analysis results shown in Table 3, by using statistically significant variables, we calculate the Malmquist productivity index for EU-28 countries for the period from 2008 to 2017. The results are represented in Table 5[§]. Malmquist productivity index (Tfpch) includes both technological changing and efficiency changing. In Table 5, we can see that the Tfpch values of all DMU are generally higher than "1". Tfpch values of these countries are lower than "1", and this means that these countries show a decrease in technological (Techch) or efficiency change (Effch) on average (such as Cyprus and Croatia in technological efficiency). We can also see some countries in which pure efficiency value (Pech) is higher than "1" by far (such as Bulgaria and Romania). It means that these countries have an increase in their managerial improvement. On the other hand, technologically efficient (Techch) values of twenty countries are lower than "1" in reducing CO_2 emissions in aviation amongst all EU-28. Since the time dimension of the data is short, it is expected that countries may have problems adapting to new technological aircraft in this short period. Therefore, this result is an expected situation. It is also observed that the technical efficiencies (Effch) of all countries increased in this period. Additionally, we can also say that all EU-28 countries perform their operations at an optimum level since their scale efficiencies (Sech) are almost equal and greater than 1.

Based on these five criteria, Bulgaria is seen as the country that has made relatively the highest progress in terms of efficient CO_2 reduction in aviation. When we check the descriptive statistics of CO_2 emission in aviation, we observe that the average amount of emissions from the aviation of Bulgaria is lower than the overall average. Although there are some countries causing lower emissions, they show less improvement than Bulgaria.

[§] Average values for 10 years are given in this table.

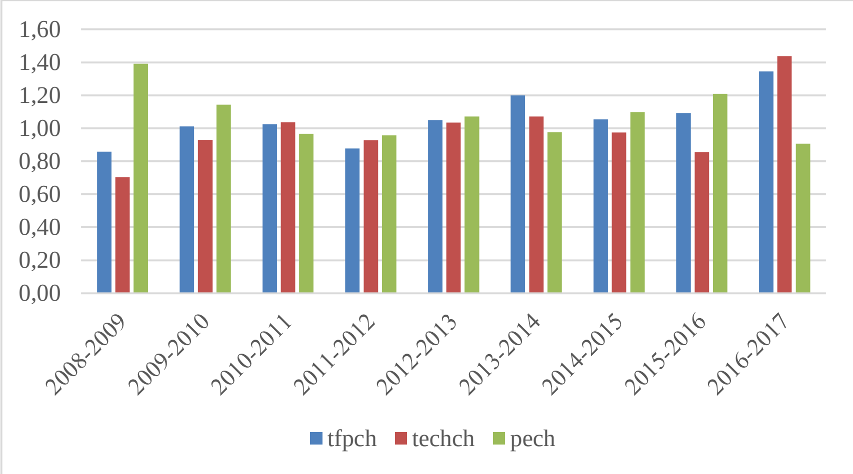

Figure 1. Averages of tfpch, techche and pech over the 2008 and 2017 for EU-28.

Figure 1 illustrates the averages of Tfpch, Techch, and Pech over the 2008 and 2017 period. We can see that there are fluctuations for all indicators in this period, which means that the EU countries have no deterministic trends for these three indicators. This result supports the results of the stochastic frontier analysis. When we evaluate the Tfpch, the average value is above “1” during the periods 2009-2010, 2010-2011, 2012-2013, 2013-2014, 2014-2015, 2015-2016, and 2016-2017. In all of these periods, technical efficiency change (Effch) leads to this increase, and this implies that there is an average increase in the reducing CO_2 efficiency in aviation in EU-28 countries while technology efficiency is low. The most efficient period in terms of technology is the 2016-2017 period.

When we examine the changes from year to year on a country-basis, we observe that Bulgaria increased its technical efficiency considerably in the 2015-2016 period. In terms of technological efficiency, we see that Estonia and Slovakia made progress in 2016 and 2017. In the 2010-2011 period, Bulgaria and Hungary made progress in terms of scale efficiency.

6. Discussion

In 2018, the ICAO council adopted the international standards and proposed practices for the implementation of ICAO's Carbon Offset and Reduction Plan for International Aviation. The pilot phase applies from 2021 through 2023 to states that have volunteered to participate in the scheme. To our knowledge, the 73 governments already signed up to CORSIA cover 88 % of aviation. The Standards and Suggested Practices adopted by ICAO were tested before the adoption of this agreement with the support of the German Government and the participation of six partner countries and ten airline companies.

The share of emissions in aviation is expected to rise by 2050 regularly, due to the increase in demand for both passenger and cargo flights, and the decrease in emissions generated by the other parts of the economy. CORSIA is one of the main tools for the growth of aviation activity without causing additional emissions. According to that, airlines will have an option to purchase emissions reductions from other sectors to offset their emissions increases above a certain level. They will be able to use offsets from, for example, the UN's Clean Development Mechanism and forestry loans. Besides the CORSIA, ICAO hopes to achieve the carbon-neutral growth target by 2020 and beyond, by taking additional measures to increase efficiency and using sustainable fuels. According to CORSIA, airline companies will be able to earn carbon credits from fossil fuels that cause fewer emissions than conventional fossil fuels. A distinction is also made between developed and developing countries, as well as between airlines with efficient and less efficient aircraft.

In this study, we examine whether European countries are ready for the CORSIA plan or not. According to the results of our analysis energy in aviation per flight, millions of passenger-kilometers, freight and mail million tonne-kilometer, total commercial aircraft fleet by age, globalization index and total number of airports are critical criteria to reduce CO_2 emission in aviation. These values should be stabilized at the optimum level for each year, starting from 2019 to achieve the implementation of

CORSIA. When there is an increase in the number of cargos, the number of passengers, and the number of aircraft types, emission values are expected to increase. However, airline companies do not tend to waive their profitability ratios by reducing these values to mitigate their emission values. The analysis result also shows that since 2008, all of the European countries have not tended to decrease their emissions significantly.

On the other hand, East European countries are found as relatively efficient in reducing CO_2 emissions in aviation. Such as Slovenia and Slovakia are found to be efficient countries based on stochastic frontier analysis, but when time dimension is involved, Bulgaria is obtained as shown most improvement country in reducing CO_2 emissions in aviation. They are efficient candidates for CORSIA conditions. However, even these countries are still not adequately prepared. The Emissions Trading System database statistics of the European Commission shows that the amounts of verified emissions generally exceed the allowances allocated free of charge amounts since 2013 for these countries (see EEA,2020). It does not contradict our results, which say that the European countries have not significantly reduced the CO_2 emissions over the years because there is no totally deterministic trend in their efficiency changes. The reason why we find these countries more efficient than other countries is due to the fact that the increase in CO_2 emissions in these countries is less than that in other countries. However, both these and other countries aim to reduce their CO_2 emissions by implementing specific policies. For example, Slovakia has introduced operational and financial planning of the use of biofuel for transport among long- and short-term plans, which are based on 2011.

Moreover, it is aimed to achieve environmental benefits in real operations at Bratislava airport. Apart from these countries, other countries are also implementing various policies to reduce emissions in aviation. The ICAO reports imply that action plans prepared by the states for Greece and Finland have been developed to reduce CO_2 emissions in the aviation sector. The Greek legislation for biofuels has been adopted since 2005. Besides, aircraft engine washes, aircraft weight reduction, route optimization, and fleet modernization reduction of flight time are aimed. Lastly, short-term and long-term targets are identified, and projects aimed at reducing emissions are introduced. In Finland, the general objectives are as follows: improving air traffic management and infrastructure use, alternative using fuels, adopting aircraft-related technology development. The implementations of more efficient operations are as below: reducing aircraft empty weight center for gravity optimization, replacing current aviation fuels with biokerosene, and creating Helsinki Airport as a “Bio-hub.”

The number of studies investigating the carbon dioxide reduction efficiency in aviation based on country data is quite low. For instance, Lu et al. (2013) investigate the CO_2 emission efficiency in OECD countries by using the input variables of industry and population and the output variances of gross domestic product and the amount of fossil-fuel CO_2 emission in the data envelopment analysis. They find that the European countries, which are Denmark, France, Greece, Iceland, Luxembourg, Norway, Switzerland, the United Kingdom, are the most efficient. As another example, Kasman and Duman (2015) examine the relationship between energy consumption, carbon dioxide emissions, economic growth, trade openness, and urbanization of new EU member and candidate countries by using panel data from 1992 to 2010. They find that there is a casual relationship from energy consumption to carbon emissions. This result is similar to our findings.

The results also point that aviation energy is highly correlated with the emission due to fuel-related effects. Because of this, some leading aircraft companies try to manufacture more fuel-efficient aircraft (such as Boeing 787 and Airbus A350). In addition to utilizing new technology, commercial flights started using sustainable alternative fuel. It is predicted that the use of alternative fuel can reduce CO_2 emissions by up to 80 % compared to traditional jet fuel (IATA, 2017). The transport sector promises a significant potential for energy efficiency through the expansion of fuel-efficient vehicles. For example, Hassan et al. (2018) use aircraft technologies, operational improvements, and sustainable biofuels for the Monte Carlo simulations, and they find that biofuels have an average 64 % effect on CO_2 emissions.

To achieve the IATA target, approximately 60 new bio-refineries are required annually by 2050 (Staples et al., 2018). Airframe and engine design (like blended-wing-body aircraft, wing-in-ground effect vehicles) and management developments (like load factors and air traffic management) are important to reduce aviation industry emissions. Related to these facts, airline companies have started to use some fuel-efficient and new technology planes such as Airbus A321-neo. These examples show that fuel-efficient airplanes will have an important role in keeping airline companies' CORSIA targets. Therefore, the companies are expected to prefer fuel-efficient aircraft in order to avoid opportunity costs of lower profits otherwise caused by reducing the number of freight or passengers to achieve CORSIA targets.

Airline companies can also use the credits of the United Nations mentioned in CORSIA implementation, or they can purchase emissions from other sectors to reduce their CO_2 emissions. In addition to these, governments can implement the white certificate system to encourage airline companies to reduce their emissions. Additionally, trading of these white certificates within the sector or across the sectors can be a good option for airlines to increase their financial profitability. Taxation on tickets (applied in some countries such as Germany, Netherlands) can also be another option, but the customers do not prefer it.

7. Conclusions

According to CORSIA, the requirements for decreasing CO_2 emissions in aviation should be applied by the participated countries. For this purpose, we aim to find significant factors affecting CO_2 emissions and determine the EU countries which are efficient in reducing CO_2 emission in aviation. By using the Eurostat data via panel data based stochastic frontier analysis, we find that energy in aviation per flight, millions of passenger-kilometers, freight and mail million tonne-kilometer, total commercial aircraft fleet by age, globalization index and total number of airports have positive and significant effects on CO_2 emissions in aviation for the EU-28 countries for 2008-2017 period. Moreover, the results of the DEA-based Malmquist productivity index indicate that Slovenia and Slovakia is relatively more efficient countries while Bulgaria has increased efficiency above the average.

When we compare the results of Stochastic frontier analysis and Malmquist productivity index, it is an advantage that the Stochastic frontier analysis shows significant variables. However, according to this analysis, although there is not much change in the efficiencies over the years, the Malmquist productivity index reveals the progress in different efficiency values. Nevertheless, as a whole, there is no increasing trend in efficiency for EU-28 countries. In this respect, this study reflects the analysis of countries in the CORSIA process. Therefore, it presents important results for airline managers and governments.

Airlines are not expected to reduce their total freight of mails, the number of passengers or the number of fleets to reduce their emissions. However, as stated in the CORSIA, fuel-efficient aircraft may be used to reduce emissions by using appropriate loans. As another option, emissions of airlines that do not meet the emission standards can be traded between airlines or across the sectors — also, government-supported tradable.

In the literature, the number of studies comparing the success of countries for reducing emissions in the aviation sector is limited. This work contributes to the literature significantly. For future studies, this study can be expanded by using different variables or making optimization in order to determine the other appropriate factors and required quantities for reducing emissions. We have worked on the total emission values in aviation in line with the purposes in CORSIA, but efficiency values can also be calculated on the carbon emissions per flight. In addition, since Malmquist productivity index is based on DEA, the results of DEA were included in this study. However, the results were not obtained as distinctive as in the stochastic frontier analysis in efficiency scores. The super-efficiency in DEA method can be tried instead of DEA, which provides better separation. Finally, since the available data for this study covered only until 2017, this study provided information about whether the countries are ready or not for CORSIA. Future research would show a clearer picture regarding the effect of CORSIA once further data is available - keeping in mind that the outlying impact of COVID-19 on the aviation industry is neutralized.

Researchers’ Contribution Rate Statement

The authors' contribution rates in the study are equal.

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Conflict of Interest Statement

The authors have no conflict of interest to disclose.

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Appendix

Table A1. Technical efficiency scores obtained from DEA

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Austria	21	25	28	31	31	27	28	29	38	30
Belgium	41	50	56	63	60	52	55	58	70	64
Bulgaria	2	1	4	1	1	1	1	1	4	1
Cyprus	1	1	1	1	1	1	1	1	1	1
Czechia	11	13	13	13	9	12	10	10	14	11
Germany	264	340	355	358	399	370	362	349	456	414
Denmark	27	31	34	37	39	35	38	36	47	40
Estonia	1	1	1	1	1	1	1	1	1	1
Greece	33	42	41	45	29	34	14	43	37	37
Spain	159	191	211	237	232	209	218	218	294	262
Finland	20	23	25	31	31	29	29	28	34	30
France	210	259	276	303	311	283	286	288	348	294
Croatia	1	3	1	1	1	1	1	1	1	1
Hungary	8	9	10	1	1	1	1	1	1	1
Ireland	28	29	32	29	26	27	30	33	42	41
Italy	118	141	158	169	169	150	154	154	199	178
Lithuania	1	1	1	1	1	1	1	1	1	1
Luxembourg	5	6	6	5	4	1	1	1	1	1
Latvia	1	1	1	1	1	1	1	1	1	1
Malta	1	1	1	1	1	1	1	1	1	1
Netherlands	108	132	137	150	151	141	148	150	187	160
Poland	14	18	18	18	24	22	25	26	34	35
Portugal	28	35	41	44	46	43	46	46	61	58
Romania	1	7	7	5	1	4	3	5	1	1
Sweden	29	32	35	39	39	37	36	35	42	26
Slovenia	1	1	1	1	1	1	1	1	1	1
Slovakia	1	1	1	1	1	1	1	1	1	1
United Kingdom	348	436	447	489	496	459	466	457	557	498