Persistent and Transient Efficiency of International Airlines

Almas Heshmati
Subal C. Kumbhakar
Jungsuk Kim

September, 2016
Persistent and Transient Efficiency of International Airlines

Almas Heshmati 1, Subal C. Kumbhakar 2 and Jungsuk Kim 3

1 Corresponding Author:
Department of Economics,
Sogang University, K526,
35 Baekbeom-ro (Sinsu-dong #1), Mapo-gu,
Seoul 121-742 Korea, and
E-mail: almas.heshmati@gmail.com

2 Department of Economics,
Binghamton University, Binghamton, NY, USA,
E-mail: kkar@binghamton.edu

3 Institute of International and Area Studies,
Sogang University, Seoul, Korea,
E-mail: iiias7@sogang.ac.kr

Abstract: This paper examines the efficiency of international airlines for the period 1998-2012 by using stochastic frontier panel data models. It estimates a four-component random error cost model for multi-output airline services, separating passenger and goods transportation at the national and international levels. The model distinguishes between firm heterogeneity, time-invariant persistent inefficiency, as well as transient (time-variant) inefficiency and random error components. This model is compared with two other models in which one of the four components is missing. All the models are estimated by using the maximum likelihood method. The models produce persistent, transient and overall efficiency for each airline and time period. The outcomes indicate that the four-component model has an advantage over the traditional panel data approach of separating airline heterogeneity and time-invariant inefficiency effects. The mean and dispersion of cost efficiency amongst airlines differ by model specifications and according to their geographical area of operations. The performance difference may be a consequence of different market structures and deregulation processes, and of specific competitive conditions such as resource availability and strategic alliances with competitors. The results confirm that in general the airlines are not able to achieve full cost efficiency. We find that carriers based in the Asia region are more efficient than carriers based in the European and North American regions. The bigger airlines are unable to take advantage of economies of scale and are not more efficient than their smaller counterparts.

Keywords: International airlines; firm heterogeneity; persistent inefficiency.

JEL Codes: C23; C51; D24; L25; L93; N70.
1. Introduction

Aviation is one of the major global industries creating more than 8.7 million jobs within the industry and contributing US$ 2.4 trillion in revenues to the world economy, which is about 3.4 per cent of the global gross domestic product (GDP).\(^1\) Since its first operations with passenger and mail services in 1903, the airline industry has undergone wide-ranging changes in keeping with fast developments in technology, expansion of the service sector and the evolution of a globalized world economy.

According to a 2011 International Air Transport Association’s (IATA) report on air travel trends over the last 40 years, the volume of air travel worldwide, measured in aggregated revenue passenger kilometers (RPKs), expanded more than ten-fold and the total cargo volume grew 14-fold. This rapid expansion took place despite repeated disruptions, including economic recessions, economic and energy crises and various global problems such as epidemics (AIDS, SARS, Avian Flu, Swine Flu, Ebola and MERS), environmental degradation, natural catastrophes, volcanic eruptions and terrorism (IATA, 2011; Pearce, 2012).

While airlines expanded exponentially in terms of handling capacity and increasing flying routes, most airlines were unsuccessful in recouping the costs of their capital over the airline business cycle of eight to ten years. This despite large investment programs undertaken by national governments in infrastructure like airports, security, communication and land transportation, which do not add to the airlines’ operating costs. Several empirical studies and reports by the Airlines Industry Association (AIA) indicate that the poor profitability of the airline industry is not due to lack of efforts on the part of the airlines; rather it is due to the specific market structure of the industry and national and international policy changes that take a heavy toll on airlines’ profitability.

Airlines so far have made many attempts to streamline their operations in order to reduce operating costs by outsourcing maintenance and ground handling, cutting down on unnecessary services offered, using advanced information and communication technologies and implementing advanced management systems. In addition, airlines have often sought to better their productivity by increasing aircraft utilization rates, adding extra revenue streams,\(^2\) bringing in a broad range of customer loyalty programs and establishing alliances or code-sharing agreements. All these cost-reducing and revenue-increasing efforts have contributed to lower operation costs and higher profitability. However, the margin above the cost still lags far behind that of other industries competing for the same sources of investment capital (IATA, 2012).

To analyze the airlines’ performance, we employed an approach in which the objective of firms is to minimize the cost of producing a given level of output or services with given factor input prices and technology. The cost function approach is attractive as demand for services and input prices are exogenously given and the airlines deal with a large number of services such as passengers, goods and mail. Thus, a production function approach might not be appropriate although based on the duality theory the cost and production function

---

\(^2\) For example, airlines are selling in-flight duty free goods on flights.
approaches should yield the same equilibrium conditions.\(^3\)

Given that the airline industry has improved tremendously in terms of production (Oum et al., 2005; Parast and Fini, 2010), we focus on another key phenomenon—the cost inefficiency that airlines are facing. We identify the factors that can cause lower inefficiency and poor profitability of the industry and, conversely, the elements that can enhance the airlines’ cost efficiency.

The rest of this paper is organized as follows. Section 2 provides a literature review on airlines’ performance. Descriptions of data and variables are given in Section 3. Section 4 gives the models that are specified and estimated. The estimations and results are compared and discussed in Section 5. Section 6 summarizes the results and provides a conclusion.

2. Literature Review

A survey of recent literature shows a large number of empirical studies that examine the factors affecting airlines’ cost efficiency (see Inglad et al., 2006; Mallikarjun, 2015; Oum et al., 2005). Allocative efficiency has drawn extensive debates among scholars (for example, Capobianco and Ferandes, 2004; Demydyuk, 2012; Good et al., 1993; Lee and Worthington, 2014). A number of efficiency studies have been done on US carriers (Assaf, 2009; Barros et al., 2013; Bhadra, 2009; Choi et al., 2013; Greer, 2008, 2009; Lu et al., 2014; Mallikarjun, 2015; Zhu, 2011) and on European-based airlines (Assaf and Josiassen, 2012; Barros and Couto, 2013; Barros and Peytoch, 2009; Duygun et al., 2015; Market and Williams, 2013; Sickles et al., 2002). Some studies cover other regions, particularly Asia (Chau and Chen, 2006; Tavassoli et al., 2014) while some study international airlines (Barbot et al., 2008; Chang et al., 2014; Coelli et al., 1999; Hong and Zhang, 2010; Inglad et al., 2006; Merkert and Hensher, 2011; Oum and Yu, 1998; Wu and Liao, 2014). With China emerging as a major actor in the airline industry, equally with other industries Asian airlines also deserve due attention through diverse researches that reflect trends of a substantial and growing share of international passenger and freight traffic.

Methodologically, there is an obvious pattern in existing studies in that they are largely confined to non-parametric estimations of allocative efficiency. A number of studies are based on stochastic frontier cost and production functions, a data envelopment analysis (DEA) and the Malmquist productivity analysis. Depending on the aim of the study, the results derived from the frontier function are used in the second stage with a different methodological approach to explain possible causes of inefficiency. These studies try to identify the various factors affecting key issues such as cost factors, profits and output. The second step approach has been proved to be wrong (Battese and Coelli, 1995; Schmidt, 2011; Wang, 2002).

Oum and Yu (1998) compared unit cost competitiveness of the world's 22 major airlines over the period 1986-93. They estimated a cost function and decomposed the unit cost differentials between airlines into potential sources. In another study, Oum et al., (2005)

\(^3\) See Varian (1994) for a detailed discussion of the duality between cost and production functions.
compared the performance of ten major North American airlines in terms of residual total factor productivity (TFP), cost competitiveness and residual average yields during the period 1990–2001. Barbot et al., (2008) studied the efficiency and productivity of 41 international airlines by grouping them into four regions.\textsuperscript{4} The authors compared the efficiency and productivity of full-service carriers with low-cost carriers. For an empirical analysis, two different methodologies — DEA and TFP — have been used (Bhadra, 2009; Chang et al., 2014; Chiou and Chen, 2006; Greer, 2008; Hong and Zhang, 2010; Lu et al., 2014; Wu and Liao, 2014).

The results of Merket and Hensher’s study (2011) show that not only the size of the airline, but also the fleet mix of the size of aircraft and the number of families of aircraft in the fleet have an impact on technical, allocative and, ultimately, cost efficiency of an airline. Although stage length has an impact on an aircraft’s unit cost, its impact at the airline level is limited to technical efficiency.

Conversely, the age of the fleet had no significant impact on technical efficiency, but it delivered, on average, a small positive effect on the allocative and cost efficiency components. An analysis of individual airlines’ efficiency scores yields examples of very young fleets achieving relatively high efficiency. Merkert and Hensher (2011) conclude that airlines’ managements that aim to reduce costs should focus less on stage length and fleet age and more on other variables, particularly the optimization of the fleet mix. They indicate that the effects of route optimization are limited to technical efficiency. Many of the works quoted here indicate the importance of identifying factors influencing airlines’ operations.

Gudmundsson (2004) examined factors associated with airline performance through an exploratory factor analysis. Parast and Fini (2010) investigated the effects of both quality and productivity on profitability in the US airline industry using panel data from 1989 to 2008. Their results show that labor productivity was the most significant predictor of profitability, while on-time performance had no relationship to profitability. The findings identified ‘labor productivity, gas price, average annual maintenance cost, and employee salary’ as the most significant explanatory variables of profitability in the industry. Using a profit function approach, Orcholski (2011) investigated profit maximization objectives of US airlines by estimating dynamic panel regression as suggested by Arellano and Bond (1991). According to them, the first order conditions can be derived from profit functions and the competitive quantities of airline seats derived from Cournot and collusive structures can be estimated.

3. Data and Variables

For an analysis of empirical performance, we employed 39 airlines’ data from 33 countries for the period 1998–2012. Airlines incur several types of expenses. Due to limited access to disaggregate and service-specific expenses data, we considered airlines’ total operating

\textsuperscript{4} They grouped airlines by using IATA’s regional classification. The regions and their respective number of airlines are Europe and Russia (21 airlines), North America and Canada (11), China and North Asia (8), Asia Pacific (7) and Africa and Middle East (2).
expenses for each year as representing total cost. This covered airlines’ total expenditure for the given year and all business activities of individual airlines were insured by this account. Having employed aggregate expenses as a dependent variable, the output parameters should comprise both passenger and cargo outputs from international and domestic flights on scheduled and non-scheduled itineraries. Table 1 provides summary statistics of the variables of the cost frontier function.

Table 1. Summary Statistics of Airlines’ Cost Data (NT=582 observations)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST</td>
<td>5,825,112</td>
<td>6,268,258</td>
<td>34,079</td>
<td>34,900,000</td>
</tr>
<tr>
<td>OUTPUT</td>
<td>7,152,631</td>
<td>6,178,128</td>
<td>139,692</td>
<td>33,900,000</td>
</tr>
<tr>
<td>WAGE</td>
<td>35,115</td>
<td>17,906</td>
<td>4,097</td>
<td>68,374</td>
</tr>
<tr>
<td>STAGE</td>
<td>408,181</td>
<td>308,896</td>
<td>-</td>
<td>1,667,315</td>
</tr>
<tr>
<td>FREQ</td>
<td>226,583</td>
<td>204,409</td>
<td>7,447</td>
<td>994,559</td>
</tr>
<tr>
<td>AC</td>
<td>180</td>
<td>133</td>
<td>40</td>
<td>827</td>
</tr>
<tr>
<td>LF</td>
<td>0.73</td>
<td>0.06</td>
<td>0.50</td>
<td>0.85</td>
</tr>
<tr>
<td>MS</td>
<td>0.02</td>
<td>0.01</td>
<td>-</td>
<td>0.06</td>
</tr>
<tr>
<td>AGEAIR</td>
<td>55</td>
<td>21</td>
<td>1</td>
<td>93</td>
</tr>
<tr>
<td>AGEAC</td>
<td>9.55</td>
<td>2.73</td>
<td>5.10</td>
<td>14.90</td>
</tr>
</tbody>
</table>

A. Operating costs

The dependent variable (COST) for the cost model is the annual operating expenses of airlines. We obtained data and information from the Korean government’s official statistics site (www.airportal.go.kr) and from each airline’s home page. Operating expenses include the costs for handling passengers, fuel, aircraft maintenance charges, catering, cargo, excess baggage and other transport-related costs\(^5\) of both scheduled and non-scheduled services. In order to resolve the data contamination problem of monetary variables from the effect of both temporal and spatial price variations, we transformed the monetarily measured variables using the consumer price index to adjust for the annual inflation\(^6\) rate of each country.

B. Explanatory variables

The stochastic frontier cost function application requires that the number of explanatory variables be kept at a reasonable level; here we considered several explanatory variables (X) including a time trend. For inefficiency measurement, depending on the model we used a different set of Z-variables including regions, alliances and time trends. The use of time trend

---

\(^5\) Includes airport fees, landing fees and ground handling charges.

\(^6\) Annual inflation data obtained from [www.imf.org](http://www.imf.org).
in the cost function represents a shift in the cost function or a technological change over time, while it represents a change in inefficiency over time in the inefficiency effects model.

Output (RTK_INT, RTK_DOM, FTK_INT, FTK_DOM and MAIL): Output is grouped into passenger, goods and mail services. We employed tonne kilometers of passengers, cargo and mail of both international and domestic flights as output measures. The output used here refers exclusively to the final output. We need to measure output with a uniform unit per different types of service production; thus tonne kilometer is the only measurement that represents all outputs of passenger, cargo and mail services. Coelli et al. (1999) argue that the use of tonne kilometers best reflects the ticketing and marketing aspects of airlines, while Lee and Worthington (2014) use available tonne kilometers (ATK) as an aggregate measure of airlines’ output. Besides these, there are many other output measurements such as revenue passenger kilometers (RPK) and revenue miles or distance flown. Lee and Johnson (2012) used both RPK and available seat kilometers (ASK) as output measures of airlines’ in a cost-based efficiency estimation study. Assaf and George (2009); Barbot et al. (2008); Greer (2009); Merkert and Hensher (2011); and Wang et al. (2011) used available seat kilometers (ASK) as one of the output measures in efficiency or productivity studies.

Wages (WAGE): One of the main input costs is labor cost which includes costs for all kinds of airline staff such as cockpit crew, cabin crew, maintenance staff, marketing personnel and airport staff. It is widely known that airline staff wages are comparatively higher than the wages of other occupation groups. This is especially true for cockpit crew that has high demand in the market. However, due to limited information, unavailability of the data needed and a large number of professions involved in airline operations, we could not access real data; instead we used the GDP per capita workforce (in constant 1990 PPP $) of the airlines’ respective home countries as a proxy for wages of airline staff. In a study on US carriers’ profitability, Parast and Fini (2010) used the actual salary data on US carriers because US carriers give such information to the public while most international carriers seldom disclose their salary information.9

Time trend (TREND) and its square: In order to capture the shift in cost over time representing technological changes, we included the time trend and its square as explanatory variables in the cost model specifications. The trend captures the direction of the change, while the squared trend captures the non-linear shift in the cost function over time.

C. Airlines’ characteristics

The set of variables representing the airlines and their market characteristics can appear in the cost model relation as determinants of cost, inefficiency or both as determinants and conditioning variables. In this study we used them to explain the patterns of airline-specific

7 Cargo output includes mail services.
8 GDP per person employed is defined as gross domestic product (GDP) divided by total employment in the economy; the purchasing power parity (PPP) index was used to convert the variable to 1990 constant international dollars using PPP rates (www.worldbank.org).
9 Thus many studies that use actual wage data are centered on the US airlines market only.
inefficiency. The set of characteristic variables are defined as:

Aircrafts (AC): The number of aircraft is used for measuring airlines’ capital assets and service production capacity. Since financial information on airlines such as their current capital assets is not readily available, the number of aircraft is applied as a proxy for airlines’ capital assets. Existing studies such as Assaf (2009), Lee and Johnson (2012) and Merkert and Hensher (2011) use the same variable as a proxy for capital input in estimating the production efficiency of airlines. This is motivated by non-aircraft capital, which is proportional to the number of aircraft, and average aircraft are assumed to be of a similar size and quality which is a strong assumption. If available, the value of aircraft after adjustment for depreciation would be a better measure of capital.

Stage (STAGE): Since financial information such as current capital assets of airlines is not readily available for research use, Bhadra (2009) used the number of seats per aircraft and the aircraft utilization rate in hours as input variables. We use the regular flight stage length as a proxy of airlines’ size. Airlines have a series of aircraft that differ in terms of seat numbers, engines, flying capability, cargo space in the belly and fuel consumption. Thus, just adding up the total number of aircraft cannot provide us comparable information on airlines’ size or capital assets. Given data availability, we consider that flying hours can be one of the proxies for this input because in order to fly longer hours, airlines need to operate many destinations including long-distance ones. Distance, frequency or airline destinations can also be used as a proxy and our result with flight hours (FHRS) produced the most significant and robust estimation.

Flight frequency (FREQ): Tsekeris (2009) and Parast and Fini (2010) used flight frequency as an input variable to measure airlines’ efficiency and productivity. This characteristic variable also measures the demand intensity for airline services.

Load factor (LF): The load factors of both international and domestic passenger flights are included here to measure productivity. ‘Airlines operating with a high load factor coefficient would expect to have a stronger demand, and thus consequently a higher production/efficiency’ (Assaf et al., 2009). At the same time, airlines’ productivity is closely related to the revenues realized per supplied capacity. Studies such as those by Assaf et al. (2009); Graham (1983); Parast and Fini (2010); and Johnson and Ozment (2011) include the load factor in the modeling of airline productivity and efficiency analyses.

Market share (MS): We used passenger market shares in the international market. Market share is one of the decisive indicators for measuring the global competitiveness of a firm in any industry. Adding passenger market share on international routes as an inefficiency variable enables us to see whether an airline’s global competitiveness departs from cost efficiency. Assaf (2009); Clougherty (2009); and Cosmas et al. (2013) used market share in estimating airlines’ efficiency.

Age of aircraft (AGE): Greer (2009) and Merkert and Hensher (2011) used aircraft age to investigate the impact of average years of operations on airlines’ productivity. Airlines equipped with new fleets and reduced average years of aircraft operations need huge investments for procurement, which affects their relative investment allocations to other
services. Hence, both positive and negative effects are expected from the use of aircraft age, and we test the direction of the effect.

Alliance (ALLIANCE): Includes four alliances grouped into One World, Star Alliance, Sky team and No Alliance. Most airlines in our study belong to major alliances such as One World, Star Alliance and Sky Team. In order to assess the impact of joining an alliance on cost efficiency—for example, by sharing a network and expanding membership programs— alliance dummies are included in the model using ‘No Alliance’ as a reference group. Barros and Peyoch (2009) also estimated alliance network effects on airline efficiency.

Region (REGION): Airlines are grouped into three regions based on their home country to see if there are significant differences across regions (for details of airlines and their home countries and regions of operations see Appendix A1).

4. Stochastic Frontier Cost Models

A. Preliminaries

Panel data stochastic frontier models introduced in the early 1980s (Battese and Coelli, 1988; Kumbhakar 1987; Pitt and Lett, 1981; Schmidt and Sickles, 1984) assumed technical inefficiency to be individual-specific and time-invariant. That is, inefficiency levels may be different for different producers, but they do not change over time, meaning that an inefficient producer never learns to improve its performance over time. This might be the case in some situations where, for example, soil quality is low and farms lack water sources for irrigation, or inefficiency is associated with managerial abilities and there is no change in management and production technology for any of the firms during the period of the study. This seems unrealistic, particularly when market competition is taken into account. Another drawback of this approach is that firm heterogeneity cannot be distinguished from inefficiency: all time-invariant heterogeneity is confounded by inefficiency.

Going forward, models were developed to include both time-invariant effects and time-varying inefficiencies. The question is: Should one view the time-invariant effects as persistent inefficiencies as in Kumbhakar (1991); Kumbhakar and Heshmati (1995); and Kumbhakar and Hjalmarsson (1993, 1998) or as firm-heterogeneity that captures the effects of (unobserved) time-invariant covariates and as such is unrelated to inefficiency (Greene, 2005a)? In both cases the cost model is written as:

\[ c_{it} = x_{it} \beta + v_{it} + \alpha_i + u_{it}, \]

where \( c \) is the logarithm of cost and \( x \) is the cost drivers (log of output(s) and input prices plus other exogenous/control variables such as the time trend that can affect cost) for firm \( i \) observed at time \( t \). Note that since we use a translog model in our empirical models, the \( x \) vector includes log of cost drivers, their squares and cross product terms. In the models used by Kumbhakar and associates (cited earlier) in the 1990s, \( \alpha_i \geq 0 \) is interpreted as persistent inefficiency, whereas Greene (2005a) views \( \alpha_i \) as firm-effects (firm heterogeneity) as in standard panel data models. The transient inefficiency component \( (u_{it}) \) is present in both models. Here we consider both specifications. In particular, we consider models in which
inefficiency is time-varying irrespective of whether the time-invariant component is treated as inefficiency or firm heterogeneity. Thus, the model we focus on is:

\[ c_{it} = \alpha_i + x_{it}^{'} \beta + v_{it} + u_{it}. \]

Compared to a standard panel data model (Baltagi, 2013; Hsiao, 2014), we have the additional transient cost inefficiency term, \( u_{it} \), in equation (2). If one treats \( \alpha_i = 1, 2, ..., N \) as a random variable that is correlated with \( x_{it} \) but does not capture inefficiency, then this model becomes what has been termed the ‘true fixed-effects’ or the ‘true fixed-effects panel stochastic frontier’ model (Greene, 2005b). The model is labeled as the ‘true random-effects’ stochastic frontier model when \( \alpha_i \) is treated as random and uncorrelated with \( x_{it} \). Note that the only difference in these specifications as compared to the models proposed by Kumbhakar and coauthors mentioned earlier is in the interpretation of the ‘time-invariant’ term, \( \alpha_i \).

Although several of the models discussed earlier can separate firm heterogeneity from transient inefficiency (which is either modeled as the product of a time-invariant random variable and a deterministic function of covariates or distributed i.i.d. across firms and over time), none of these models consider persistent technical inefficiency. Identifying the magnitude of persistent inefficiency is important, especially in short panels because it reflects the effects of inputs like management (Mundlak, 1961) as well as other unobserved inputs which vary across firms but not over time. Thus, unless there is a change in something that affects management practices at the level of the firm (such as changes in ownership or new government regulations), it is unlikely that persistent inefficiency will change. Alternatively, transient inefficiency can change over time without operational changes in a firm.

**B. Model 1: Firm effects treated as persistent inefficiency**

To help formalize this issue of persistent inefficiency versus firm heterogeneity more clearly we consider the following model:

\[ c_{it} = \beta_0 + x_{it}^{'} \beta + \epsilon_{it} = \beta_0 + x_{it}^{'} \beta + v_{it} + (u_i + \tau_{it}) \]

which we label Model 1. Note that we have replaced \( \alpha_i \) by \( \beta_0 + u_i \). The error term, \( \epsilon_{it} \), is decomposed as \( \epsilon_{it} = v_{it} + u_i + \tau_{it} \) where \( v_{it} \) is statistical noise, \( u_i \) is persistent inefficiency (for example, time-invariant ownership/management) and \( \tau_{it} \) is the transient component of technical inefficiency, both of which are non-negative. The former is only firm-specific, while the latter is both firm- and time-specific. This model has been proposed by Kumbhakar and Heshmati (1995) and Kumbhakar and Hjalmarsson (1998).

Such a decomposition of inefficiency is desirable because when \( u_i \) does not change over time and if a firm or government wants to improve efficiency then some change in management needs to take place. Alternatively, \( u_i \) also does not fully capture inefficiency
because it does not account for inefficiency that can change over time. The transient component can capture this component. In this model the size of overall inefficiency as well as the components are important to know because they convey different information. Thus, for example, if the transient inefficiency component for a firm is relatively large in a particular year then it may be argued that inefficiency is caused by something which is unlikely to be repeated in the next year. On the other hand, if the persistent inefficiency component is large for a firm, then it is expected to operate with a relatively high level of inefficiency over time, unless some changes in policy and/or management take place. Thus, a high value of $u_t$ is of more concern from a long term point of view because of its persistent nature than a high value of $\tau_t$.

The advantage of Model 1 is that one can estimate all the parameters, except the intercept, consistently without assuming any distribution on the error components. This can be seen by rewriting the model as:

$\mathbf{c}_t = \mathbf{[} \beta_0 - u_t - E(\tau_t) \mathbf{]} + x_t\beta + v_t - \{ \tau_t + E(\tau_t) \} \equiv \beta_0^* + x_t\beta + \omega_t \mathbf{.}$

The error term $\omega_t = v_t - \{ \tau_t + E(\tau_t) \}$ has zero mean and constant variance. Thus, the model in equation (4) fits perfectly with the standard panel data model with firm-specific effects (one-way error component model), and can be estimated either by the least-squares dummy variable (LSDV) approach (under the fixed effects framework) or by generalized least-squares (GLS) (under the random effects framework).

C. Model 2: Firm effects treated as firm heterogeneity

As mentioned earlier if one treats $\alpha_i, i=1,2,...,N$ as a fixed variable that is correlated with $x_t$ but does not capture inefficiency, then the earlier model becomes what has been termed the ‘true fixed-effects’ panel stochastic frontier model (Greene, 2005a, 2005b). The model is labeled as the ‘true random-effects’ stochastic frontier model when $\alpha_i$ is treated as random and uncorrelated with $x_t$. We label this Model 2. Note that the main difference between Models 1 and 2 is in the interpretation of firm-effects. If these firm-effects are treated as inefficiency, the overall inefficiency will be bigger. That is, ceteris paribus, inefficiency (overall) in Model 1 is likely to be higher than that in Model 2.

D. Model 3: Separation of firm heterogeneity from persistent inefficiency

Given the backdrop of Models 1 and 2, we introduce the model of Colombi et al. (2014); Kumbhakar et al. (2014); and Tsionas and Kumbhakar (2014) that overcomes several limitations of these models. In this model the error term is split into four components to take into account different factors affecting cost, given the outputs quantities and input prices. The first component captures firms' latent heterogeneity (Greene, 2005a, 2005b), which has to be separated from inefficiency; the second component captures transient inefficiency. The third component captures persistent or time-invariant inefficiency as in Kumbhakar and
Heshmati (1995) and Kumbhakar and Hjalmarsson (1998) while the last component captures random shocks. This model (labeled as Model 3) is specified as:

\[
c_{it} = \beta_0 + x_i'\beta + \mu_i + \eta_{it} + \nu_{it} + u_{it}
\]

The two components \( \eta_i > 0 \) and \( u_i > 0 \) reflect persistent and transient inefficiency respectively, while \( \mu_i \) captures unobserved, time-invariant firm heterogeneity and \( \nu_{it} \) is the classical random noise. We also refer to this model as the generalized TRE because it is a generalization of the true random effects (TRE) model (Model 2).

Model 3 improves upon the previous two models in several ways. First, although some of the transient inefficiency models presented earlier can accommodate firm effects, these models fail to take into account the possible presence of some factors that might have permanent effects on a firm's inefficiency. Here we call them persistent components of cost inefficiency. Second, stochastic frontier models allowing transient inefficiency assume that a firm’s inefficiency at time \( t \) is independent of its previous level of inefficiency. It is more sensible to assume that a firm may eliminate a part of its inefficiency by removing some of the short-run rigidities, while some other sources of inefficiency might stay with the firm over time. The former is captured by the time-invariant component, \( \eta_i \), and the latter by the transient component, \( u_{it} \). Finally, many panel models do consider persistent/time-invariant inefficiency effects, but they do not take into account the effect of unobserved firm heterogeneity on cost. By doing so, these models confound persistent/time-invariant inefficiency with firm effects (heterogeneity). Models proposed by Greene (2005a, 2005b); Chen et al. (2014); and Kumbhakar and Wang (2005) decompose the error term in the function into three components: a producer-specific transient inefficiency term; a producer-specific random or fixed effects capturing latent heterogeneity; and a producer- and time-specific random error term. However, these models consider any producer-specific, time-invariant component as unobserved heterogeneity. Thus, although firm heterogeneity is now accounted for, it comes at the cost of ignoring persistent inefficiency. In other words, persistent inefficiency is again confounded with latent heterogeneity.

E. Special cases of Model 3

Many interesting stochastic frontier panel data models can be obtained as special cases of Model 3 (equation 5) by eliminating one or more of the random components. For a somewhat easy reference to all these models, Colombi et al. (2014) consider a three letter identifier system where each identifier refers to an error component. Since every model contains a random shock component we do not put an identifier for it. Thus, although we have a maximum of a four-way error components model a three letter model identifier is used. The first letter in the identifier pertains to the presence (T=True) or absence (F=False) of random firm (cross-sectional unit) effects in the model; the second letter (again, T or F) is related to the presence/absence of the transient inefficiency term; and the third letter indicates the presence/absence of the time-invariant (persistent) inefficiency term. Using this system, the four-component model in equation (5) is labeled as TTT. Greene's true random-effect model
(2005a, 2005b) is obtained by dropping the $\eta_i$ term from equation (5) and it is labeled as TTF. Similarly, the Kumbhakar and Heshmati (1995) model, which accommodates both transient and persistent inefficiency terms but not latent firm heterogeneity, is labeled as FTT. The Battese and Coelli (1988); Kumbhakar (1987); Pitt and Lee (1981); and Schmidt and Sickles (1984) and time-invariant inefficiency models are obtained by dropping $\mu_i$ and $u_{it}$ terms and are labeled as FFT. Pitt and Lee’s (1981) pooled model is labeled as FTF (that is, $b_t$ and $\eta_i$ are dropped). Within this nomenclature, we could also have TFT, a model which accommodates latent firm heterogeneity and persistent (time-invariant) inefficiency, but not transient inefficiency (by omitting $u_{it}$).

F. Estimation procedure

F1. Multi-step estimation method

Estimation of the model in equation (5) can be done in a single stage ML method based on distributional assumptions on the four error components (Colombi et al., 2014). Here, we first describe a simpler multi-step procedure suggested by Kumbhakar et al. (2014) before discussing the full maximum likelihood estimation. The purpose of this is to show that the parameters of the TTT model are identified. Also one can separate persistent inefficiency from random airline effects (noise). To do so, we rewrite the model in equation (5) as:

$$
\epsilon_{it} = \beta_0 + \beta \tilde{x}_{it} + \alpha_i + \nu_{it}
$$

where $\beta_0 = \beta_0 - E(\eta_i) - E(u_{it})$; $\alpha_i = \mu_i - \eta_i + E(\eta_i)$; and $\nu_{it} = \nu_{it} - u_{it} + E(u_{it})$. With this specification $\alpha_i$ and $\nu_{it}$ have zero mean and constant variance. This model can be estimated in three steps:

**Step 1:** Since equation (6) is the familiar panel data model, in the first step the standard random effect panel regression is used to estimate $\hat{\beta}$. This procedure also gives predicted values of $\hat{\alpha}_i$ and $\hat{\nu}_{it}$, which we denote by $\hat{\alpha}_i$ and $\hat{\nu}_{it}$.

**Step 2:** In the second step, the transient technical inefficiency $u_{it}$ is estimated. For this we use the predicted values of $\nu_{it}$ from Step 1. Since:

$$
\nu_{it} = v_{it} - u_{it} + E(u_{it})
$$

by assuming $v_{it}$ is i.i.d. $N(0, \sigma_v^2)$ and $u_{it}$ is $N^+(0, \sigma_u^2)$, which means $E(u_{it}) = \sqrt{2\pi} \sigma_u$, and ignoring the difference between the true and predicted values of $\nu_{it}$ (which is the standard practice in any two- or multi-step procedure), we can estimate equation (6) by using the standard stochastic frontier technique. This procedure predicts the transient technical inefficiency components following Jondrow et al. (1982) or transient technical efficiency (RTE) (Battese and Coelli, 1988).
Step 3: In the final step we can estimate \( \eta_i \) following a similar procedure as in Step 2. For this we use the best linear predictor of \( \alpha_i \) from Step 1. Since:

\[
\alpha_i = \mu_i - \eta_i + E(\eta_i),
\]

By assuming \( \mu_i \) is i.i.d. \( N(0, \sigma_\mu^2) \), \( \eta_i \) is i.i.d. \( N^*(0, \sigma_\eta^2) \), which in turn means \( E(\eta_i) = \sqrt{2 \pi} \sigma_\eta \), we can estimate equation (8) by using the standard normal-half normal stochastic frontier model cross-sectionally and obtain estimates of the persistent technical inefficiency components, \( \eta_i \), using the Jondrow et al. (1982) procedure. Persistent technical efficiency (PTE) can be estimated using the formula in Battese and Coelli (1988). Overall technical efficiency, OTE, is then obtained from the product of PTE and RTE, that is, \( OTE_{it} = PTE_{it} \times RTE_{it} \).

F2. Maximum likelihood estimation method

We now describe an estimation of the four-component model via maximum likelihood estimation (MLE) first proposed in Colombi et al. (2014). Filippini and Greene (2016) used simulated ML that avoids some problems inherent in using the classical ML method.

A Single-step Maximum Likelihood Method: While Kumbhakar et al.’s (2014) multi-step approach discussed earlier allows one to control for latent firm effects and transient and persistent inefficiency, it still imposes distributional assumptions in the last two steps and is inefficient relative to the single-step MLE. However, given the structure of the four error component model we need to discuss how we can specify distribution for each component to ensure identification. For this we turn to the closed-skew normal distribution.

To obtain a tractable likelihood function, Colombi et al. (2014) used a skew normal distribution property for both the transient \( (v_{it} + u_{it}) \) and time-invariant \( (\mu_i + \eta_i) \) random components of equation (5). Assuming \( v_{it} \) is i.i.d. standard normal and \( u_{it} \) is i.i.d. half normal, the composed error \( v_{it} + u_{it} \) has a skew normal distribution. The same set of assumptions on \( \mu_i \) and \( \eta_i \) makes \( (\mu_i + \eta_i) \) the skew normal. Finally, the sum of two independent skew normal random variables follows a closed skew normal distribution which is used to derive the likelihood function in equation (5) (see Colombi et al., 2014 for details), which can be maximized to obtain MLE of all the parameters.

Aside from estimating \( \beta \) and the parameters of the distribution of random components, we still need to construct predictors of technical inefficiency and firm effects. Using the moment generating function, Colombi et al. (2014) provide the conditional means of random effects which are similar to the Jondrow et al. (1982) estimator of \( \mu_i \).

B. Simulated Maximum Likelihood Method: While the log-likelihood of the TTT stochastic frontier model appears daunting to implement, Filippini and Greene (2016) have proposed a simulation based optimization routine which circumvents many of the challenges with brute force optimization in this setting. Using the insights of Butler and Moffitt (1982), Filippini
and Greene (2016) note that the density in Colombi et al. (2014) can be greatly simplified by conditioning on $\mu_i$ and $\eta_i$. In this case, the conditional density is simply the product over time of $T$ univariate closed-skew normal densities. Thus, only a single integral, as opposed to $T$ integrals needs to be calculated. Maximization of this simulated log likelihood is not more complicated than the cross-sectional case, aside from the additional parameters. To estimate Model 3 here we follow the procedure in Filippini and Greene (2016).

Since Model 3 (TTT) generated Model 1 and Model 2 as special cases, one can do a likelihood ratio test to test which model is more appropriate for the data. The LR test rejects both Models 1 and 2 (at the 1 per cent level of significance) when each is tested against Model 3. In the next section we give the results from all three models, although Models 1 and 2 are rejected. This is done to check the robustness of the results.

5. An analysis of the results

First, we report (in Table 2) efficiency results (in percentile form) from Model 1 (KH) in which the overall efficiency (KH_Overall) is a product of persistent (KH_P) and transient efficiency (KH_R) components. The persistent efficiency component resulting from time-invariant ownership/policy/management is lower with a larger dispersion, while the opposite is true for the transient component. Since the KH model does not separate airline-effects (heterogeneity) from persistent inefficiency, parts of airline-effects will be confounded in persistent inefficiency. Consequently, the KH model is likely to generate estimates of persistent efficiency that are biased downwards. We find large variations in persistent efficiency with a mean of 77.76 per cent. On the other hand, variations in transient efficiency are much lower and their mean is 93.71 per cent. The overall efficiency is lower because of low persistent efficiency. The mean overall efficiency is 72.92 per cent.

<table>
<thead>
<tr>
<th>Percentiles</th>
<th>KH_P</th>
<th>KH_R</th>
<th>KH_Overall</th>
<th>TC_KH</th>
<th>RTS_KH</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0100</td>
<td>0.6108</td>
<td>0.8630</td>
<td>0.5554</td>
<td>-0.1865</td>
<td>0.8923</td>
</tr>
<tr>
<td>0.0500</td>
<td>0.6658</td>
<td>0.9010</td>
<td>0.6225</td>
<td>-0.1568</td>
<td>0.9273</td>
</tr>
<tr>
<td>0.1000</td>
<td>0.6952</td>
<td>0.9163</td>
<td>0.6481</td>
<td>-0.1383</td>
<td>0.9472</td>
</tr>
<tr>
<td>0.2500</td>
<td>0.7240</td>
<td>0.9310</td>
<td>0.6767</td>
<td>-0.1061</td>
<td>1.0110</td>
</tr>
<tr>
<td>0.5000</td>
<td>0.7661</td>
<td>0.9416</td>
<td>0.7163</td>
<td>-0.0874</td>
<td>1.0855</td>
</tr>
<tr>
<td>0.7500</td>
<td>0.8252</td>
<td>0.9500</td>
<td>0.7739</td>
<td>-0.0687</td>
<td>1.2236</td>
</tr>
<tr>
<td>0.9000</td>
<td>0.8808</td>
<td>0.9560</td>
<td>0.8305</td>
<td>-0.0481</td>
<td>1.3606</td>
</tr>
<tr>
<td>0.9500</td>
<td>0.9325</td>
<td>0.9591</td>
<td>0.8848</td>
<td>-0.0398</td>
<td>1.4120</td>
</tr>
<tr>
<td>0.9900</td>
<td>1.0000</td>
<td>0.9629</td>
<td>0.9540</td>
<td>-0.0182</td>
<td>1.7712</td>
</tr>
</tbody>
</table>

| Mean        | 0.7776 | 0.9371 | 0.7292     | -0.0892 | 1.1286 |
| Std. Dev.   | 0.0778 | 0.0229 | 0.0796     | 0.0369  | 0.1688 |
| Observation | 582    | 582    | 582        | 582     | 582    |
Efficiency results from Model 2 are reported (in percentile form) in Table 3. Model 2 is popularly known as the true random effects (TRE) model, which does not include persistent inefficiency. Thus, airline-effects are likely to capture some of the persistent inefficiency. With no persistent inefficiency, the overall efficiency in the TRE model is the same as transient efficiency. The mean overall efficiency is 93.36 per cent which is much higher than the mean overall efficiency in the KH model. Since persistent efficiency is assumed to be 100 per cent, the overall efficiency is likely to be biased upwards. In other words, the overall efficiency in the KH model is biased downwards whereas in the TRE model it is biased upwards. The truth is somewhere in between. That is why we need Model 3 which separates the two —time-invariant inefficiency and random airline-effects (heterogeneity).

<table>
<thead>
<tr>
<th>Table 3. Results from Model 2 (TRE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentiles</td>
</tr>
<tr>
<td>0.0100</td>
</tr>
<tr>
<td>0.0500</td>
</tr>
<tr>
<td>0.1000</td>
</tr>
<tr>
<td>0.2500</td>
</tr>
<tr>
<td>0.5000</td>
</tr>
<tr>
<td>0.7500</td>
</tr>
<tr>
<td>0.9000</td>
</tr>
<tr>
<td>0.9500</td>
</tr>
<tr>
<td>0.9900</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Observation</td>
</tr>
</tbody>
</table>

The efficiency results from Model 3 (labeled as the generalized TRE or GTRE model) are presented (in percentiles) in Table 4. In this model airline-specific effects are treated as traditional firm-specific effects and are separated from persistent inefficiency. Similar to the KH model, the overall efficiency in GTRE is decomposed into persistent efficiency (GTRE_P) and transient efficiency (GTRE_R). Since this model separates persistent inefficiency from airline-effects, variations in persistent efficiency are found to be quite low. The mean persistent efficiency is quite high (97.31 per cent) as compared to the KH model. While the mean transient efficiency in the KH and TRE models is almost the same (around 93 per cent), it is much lower in GTRE (83.86 per cent).

<table>
<thead>
<tr>
<th>Table 4. Results from Model 3 (GTRE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentiles</td>
</tr>
<tr>
<td>0.0100</td>
</tr>
<tr>
<td>0.0500</td>
</tr>
</tbody>
</table>
To get a better picture of the efficiency components from different models for all airlines, we report density plots for them. In Figure 1 we plot transient efficiency components from all the three models. It is clear from the figure that the distribution of the transient components in Models 1 and 2 is almost identical (not just the means). Except for some values in the lower tail, most of the airlines are found to have high efficiency in so far as their transient efficiency is concerned. That is, if one chooses either Model 1 or 2, the conclusion will be that the airlines are performing well in their day to day operations. This is, however, not the case in Model 3. Although the distribution has a long left tail (similar to that in the KH and TRE models), its mean is about 10 per cent lower.

<table>
<thead>
<tr>
<th></th>
<th>0.1000</th>
<th>0.2500</th>
<th>0.5000</th>
<th>0.7500</th>
<th>0.9000</th>
<th>0.9500</th>
<th>0.9900</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9681</td>
<td>0.9698</td>
<td>0.9712</td>
<td>0.9729</td>
<td>0.9778</td>
<td>0.9946</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>0.7469</td>
<td>0.8057</td>
<td>0.8539</td>
<td>0.8863</td>
<td>0.9114</td>
<td>0.9274</td>
<td>0.9461</td>
<td></td>
</tr>
<tr>
<td>0.7265</td>
<td>0.7849</td>
<td>0.8290</td>
<td>0.8610</td>
<td>0.8842</td>
<td>0.9000</td>
<td>0.9153</td>
<td></td>
</tr>
<tr>
<td>-0.0683</td>
<td>-0.0390</td>
<td>-0.0178</td>
<td>0.0026</td>
<td>0.0248</td>
<td>0.0341</td>
<td>0.0546</td>
<td></td>
</tr>
<tr>
<td>0.8965</td>
<td>0.9444</td>
<td>1.0219</td>
<td>1.1312</td>
<td>1.2377</td>
<td>1.2880</td>
<td>1.3905</td>
<td></td>
</tr>
</tbody>
</table>

Mean 0.9731  0.8386  0.8159  -0.0207  1.0480
Std. Dev. 0.0068  0.0706  0.0669  0.0377  0.1298
Observation 537  537  537  537  537  537

Figure 1: Time-varying efficiency in Models 1-3
In Figure 2, we report the density plots of overall efficiency. Since the TRE model does not include persistent inefficiency, its overall efficiency is the same as transient efficiency. Further, because it ignores persistent inefficiency the overall efficiency is likely to be higher compared to the other two models. The distribution for the KH model looks similar to that of the GTRE model but its mean is pushed back by about 10 per cent. The low efficiency of the KH model is likely to be caused by the fact that it treats all time-invariant airline effects as inefficiency.

![Figure 2: Overall Efficiency in Models 1-3](image)

Efficiency estimates in all stochastic frontier models are based on the residuals. Thus, it is important to make sure that the technology is specified properly. If the estimated technology is mis-specified, the resulting residuals will be wrong which in turn is likely to give inappropriate estimates of efficiency scores. Note that the deterministic part of all the three models is exactly the same (all are translog). However, the estimated parameters differ because the error components in each model are different. Since the likelihood ratio tests reject Models 1 and 2, we treat Model 3 as the best model for the data. We calculate returns to scale (RTS) and technical change (TC) in all the three models and report the results for a robustness check. It is worth pointing out that RTS and TC are defined exactly the same way in all the three models:

\[
RTS = 1 / \left[ \partial \ln C / \partial \ln Y \right] \quad \text{and} \quad TC = \partial \ln C / \partial t
\]
where C is total cost, Y is output and t is the time trend variable. Note that both RTS and TC are observation-specific (we omitted the i and t subscripts) because the cost function is a translog. Percentiles of both RTS and TC from Models 1-3 are reported in Tables 2-4 respectively.

Although RTS is calculated from the same translog cost function, RTS estimates are different for different models. Model 1 gives the highest estimates in almost all percentiles and about 75 per cent of the airlines’ year-observations show increasing RTS, the median being 1.08. Model 2 predicts increasing RTS for about half of the airlines’ year-data points and the median is 0.95. So the prediction of Model 2 is different from Model 1 for many airlines. Estimates of RTS from Model 3 are in between. The median value of 1.022 is slightly above constant RTS. A close look at their density plot in Figure 3 shows that the distribution looks alike but is pushed to the right starting from Model 2 to Model 3 to Model 1.

TC in a cost function is technical progress if the sign is negative (meaning that *ceteris paribus* the cost decreased over time). Thus, all three models show technical progress at the mean/median, at the rate of 1.6 to 1.7 per cent per year in Models 2 and 3, and at a much higher rate of 8.74 per cent in Model 1. However, technical regress (positive value of TC) is also observed for some airlines, and their numbers are model specific. The distribution of TC (reported in Figure 4) shows that Model 1 predicts unbelievably high rates of technical progress for almost all the airlines in every year. This is not the case in Models 2 and 3, which are very similar in all percentiles. Median TC (progress) in Models 2 and 3 is 2.07 per cent per annum.
6. Summary and Conclusion

This paper estimated the cost efficiency of 39 international airlines from 33 countries. The airlines’ cost efficiency was analyzed using three state-of-the-art stochastic frontier panel data models. Our output measure took into account multi-output services at the national and international levels. The most flexible model (Model 3) accommodated an error term that had four components. The model distinguished between firm heterogeneity, time-invariant persistent inefficiency, as well as transient (time-variant) inefficiency and random error components. The other two models are special cases of Model 3. All three models were estimated by the maximum likelihood method using distributional assumptions on the error components. From the estimated persistent and transient efficiency components we computed overall efficiency for each airline and time period.

The flexible cost model used here has an advantage over the traditional frontier panel data models in separating airlines’ heterogeneity and persistent efficiency. The mean and dispersion of cost efficiency amongst airlines differ by model specifications and various airline characteristics. The performance difference can be attributed to and explained by airline and market characteristics like geographic area of operations, size of the airline, different market structures, deregulation processes, competitive conditions and strategic alliances with competitors.
Efficiency results from the model where airline-specific heterogeneity effects are confounded in persistent inefficiency (Model 1) showed that the model is likely to generate estimates of efficiency that are biased downwards. This results in relatively low mean and large dispersion in the persistent and overall components of efficiency. As expected treating airline-specific effects as firm heterogeneity (Model 2) results in similar levels of transient efficiency and in the absence of capturing persistent efficiency the overall efficiency is biased upwards. The results from these two models suggest that variations in airline-specific persistent efficiency are large reflecting accumulative improvements in transient efficiency through learning by doing over time.

The true efficiency level is somewhere in between those obtained from Models 1 and 2. In order to estimate the level of efficiency that is close to the truth, the generalized Model 3 was estimated. This model overcomes the limitations of the previous two models by using a four-component error term that allows us to capture the presence of persistent time-invariant efficiency. The model enables separating and accounting for transient efficiency and firm heterogeneity components. Since the likelihood ratio tests reject Models 1 and 2, we treat Model 3 as the best model for the data. The resulting overall efficiency level is somewhere between the first two models reducing downward and upward biases due to any mis-specification. The model results in persistent efficiency with higher mean and low dispersion as well as lower overall efficiency.

An analysis of the distribution of efficiency confirms significant heterogeneity and dispersion in the two components’ patterns. The results show much variation across airlines and over time considering learning and temporal changes in efficiency. This is confirmed by the distribution of the efficiency components. Kernel density plots show that the distribution of the transient components in Models 1 and 2 is almost identical. Most of the airlines are found to have high efficiency. The estimation results based on the generalized Model 3 overcome the limitations of the previous two models. Equality, however, is not the case in Model 3. Although the distribution has a long left tail, its mean is about 10 per cent lower.

We calculated returns to scale and technical change which are defined in the same way in all the three models and reported the results for a robustness check. The Kernel density of technical change and returns to scale specifications in general indicated similar dispersion but different concentrations. A close look at the returns to scale density plot showed that the distributions look alike but are pushed to the right starting from Model 2 to Model 3 to Model 1. The distribution of technical change shows that Model 1 predicts high rates of technical progress for almost all the airlines in every year. This is not the case in Models 2 and 3, which are very similar in all percentiles.

References


International Air Transport Association (2014). Aviation benefits beyond borders, page 2-8, [www.aviationbenefitsbeyondborders.org](http://www.aviationbenefitsbeyondborders.org)


### Appendix A1. Airlines and Countries

<table>
<thead>
<tr>
<th>Country</th>
<th>Sub Total</th>
<th>Region</th>
<th>Tone Rank</th>
<th>Pax Rank</th>
<th>Airline</th>
<th>Airline Code</th>
<th>Alliance</th>
<th>Starting Year</th>
<th>AC</th>
<th>AC Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>5 Countries</td>
<td>AM</td>
<td>1</td>
<td>1</td>
<td>American Airlines</td>
<td>AA</td>
<td>one word</td>
<td>1934</td>
<td>896</td>
<td>14.9</td>
</tr>
<tr>
<td></td>
<td>8 Airlines</td>
<td></td>
<td></td>
<td></td>
<td>UNITED airline</td>
<td>UA</td>
<td>star</td>
<td>1931</td>
<td>704</td>
<td>13.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>DELTA airline</td>
<td>DL</td>
<td>sky team</td>
<td>1929</td>
<td>722</td>
<td>16.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>US AIR</td>
<td>US</td>
<td>star</td>
<td>1939</td>
<td>339</td>
<td>12.6</td>
</tr>
<tr>
<td>Canada</td>
<td>AM</td>
<td>12</td>
<td>8</td>
<td></td>
<td>Air Canada</td>
<td>AC</td>
<td>star</td>
<td>1937</td>
<td>205</td>
<td>12.2</td>
</tr>
<tr>
<td>Brazil</td>
<td>AM</td>
<td>15</td>
<td>14</td>
<td></td>
<td>TAM Linhas Aereas</td>
<td>JJ</td>
<td>star</td>
<td>1976</td>
<td>146</td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td>AM</td>
<td>30</td>
<td>33</td>
<td></td>
<td>LAN Airlines</td>
<td>LA</td>
<td>one word</td>
<td>2004</td>
<td>107</td>
<td>5.1</td>
</tr>
<tr>
<td>Colombia</td>
<td>AM</td>
<td>31</td>
<td>42</td>
<td></td>
<td>AVIANCA</td>
<td>AV</td>
<td>star</td>
<td>1940</td>
<td>71</td>
<td>6.9</td>
</tr>
<tr>
<td>China</td>
<td>AS</td>
<td>2</td>
<td>2</td>
<td></td>
<td>Air China</td>
<td>CA</td>
<td>star</td>
<td>1988</td>
<td>275</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>China Southern</td>
<td>CZ</td>
<td>sky team</td>
<td>1988</td>
<td>259</td>
<td>6.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>China Eastern</td>
<td>MU</td>
<td>sky team</td>
<td>1989</td>
<td>413</td>
<td>6.6</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>AS</td>
<td>2</td>
<td>2</td>
<td></td>
<td>Cathay Pacific Airways</td>
<td>CX</td>
<td>one world</td>
<td>1946</td>
<td>134</td>
<td>10.3</td>
</tr>
<tr>
<td>Korea</td>
<td>AS</td>
<td>6</td>
<td>13</td>
<td></td>
<td>Korean Air</td>
<td>KE</td>
<td>sky team</td>
<td>1969</td>
<td>130</td>
<td>9.4</td>
</tr>
<tr>
<td>Japan</td>
<td>AS</td>
<td>7</td>
<td>7</td>
<td></td>
<td>Japan Airlines</td>
<td>KJL</td>
<td>one world</td>
<td>1951</td>
<td>180</td>
<td>9.5</td>
</tr>
<tr>
<td>Singapore</td>
<td>AS</td>
<td>9</td>
<td>17</td>
<td></td>
<td>Singapore Airlines</td>
<td>SQ</td>
<td>star</td>
<td>1972</td>
<td>128</td>
<td>6.4</td>
</tr>
<tr>
<td>Australia</td>
<td>AS</td>
<td>13</td>
<td>12</td>
<td></td>
<td>Qantas Airways</td>
<td>QF</td>
<td>one world</td>
<td>1922</td>
<td>141</td>
<td>10.8</td>
</tr>
<tr>
<td>India</td>
<td>AS</td>
<td>14</td>
<td>11</td>
<td></td>
<td>Air India</td>
<td>AI</td>
<td>one world</td>
<td>1932</td>
<td>88</td>
<td>7.3</td>
</tr>
<tr>
<td>Thailand</td>
<td>AS</td>
<td>18</td>
<td>19</td>
<td></td>
<td>Thai Airways</td>
<td>TG</td>
<td>star</td>
<td>1960</td>
<td>98</td>
<td>10.7</td>
</tr>
<tr>
<td>Malaysia</td>
<td>AS</td>
<td>21</td>
<td>21</td>
<td></td>
<td>Malaysia Airlines</td>
<td>MH</td>
<td>one world</td>
<td>1947</td>
<td>108</td>
<td>10.3</td>
</tr>
<tr>
<td>Indonesia</td>
<td>AS</td>
<td>26</td>
<td>23</td>
<td></td>
<td>Garuda Airways</td>
<td>GA</td>
<td>N/A</td>
<td>1950</td>
<td>81</td>
<td>6.5</td>
</tr>
<tr>
<td>Philippines</td>
<td>AS</td>
<td>29</td>
<td>28</td>
<td></td>
<td>Philippine Airlines</td>
<td>PR</td>
<td>N/A</td>
<td>1941</td>
<td>40</td>
<td>9.8</td>
</tr>
<tr>
<td>New Zealand</td>
<td>AS</td>
<td>32</td>
<td>30</td>
<td></td>
<td>Air New Zealand</td>
<td>NZ</td>
<td>star</td>
<td>1940</td>
<td>98</td>
<td>9.4</td>
</tr>
<tr>
<td>Germany</td>
<td>EU</td>
<td>3</td>
<td>4</td>
<td></td>
<td>Lufthansa,</td>
<td>LH</td>
<td>star</td>
<td>1926</td>
<td>427</td>
<td>12.3</td>
</tr>
<tr>
<td>U.K</td>
<td>EU</td>
<td>5</td>
<td>3</td>
<td></td>
<td>British Airways</td>
<td>BA</td>
<td>one world</td>
<td>1919</td>
<td>240</td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>EU</td>
<td>8</td>
<td>6</td>
<td></td>
<td>Air France</td>
<td>AF</td>
<td>sky team</td>
<td>1933</td>
<td>377</td>
<td>9.5</td>
</tr>
<tr>
<td>Spain</td>
<td>EU</td>
<td>16</td>
<td>15</td>
<td></td>
<td>IBERIA</td>
<td>IB</td>
<td>one world</td>
<td>1927</td>
<td>112</td>
<td>9.3</td>
</tr>
<tr>
<td>Ireland</td>
<td>EU</td>
<td>17</td>
<td>10</td>
<td></td>
<td>Air Lingus</td>
<td>EI</td>
<td>N/A</td>
<td>1936</td>
<td>44</td>
<td>6.7</td>
</tr>
<tr>
<td>Turkey</td>
<td>EU</td>
<td>20</td>
<td>18</td>
<td></td>
<td>Turkish Airlines</td>
<td>TK</td>
<td>star</td>
<td>1956</td>
<td>189</td>
<td>6.4</td>
</tr>
<tr>
<td>Italy</td>
<td>EU</td>
<td>22</td>
<td>22</td>
<td></td>
<td>Alitalia</td>
<td>AZ</td>
<td>sky team</td>
<td>1947</td>
<td>160</td>
<td>9.4</td>
</tr>
<tr>
<td>Switzerland</td>
<td>EU</td>
<td>23</td>
<td>25</td>
<td></td>
<td>SWISS Air</td>
<td>LX</td>
<td>star</td>
<td>1931</td>
<td>91</td>
<td></td>
</tr>
<tr>
<td>Sweden</td>
<td>EU</td>
<td>25</td>
<td>24</td>
<td></td>
<td>SAS Scandinavian Airlines</td>
<td>SK</td>
<td>star</td>
<td>1946</td>
<td>143</td>
<td>12.9</td>
</tr>
<tr>
<td>Portugal</td>
<td>EU</td>
<td>33</td>
<td>29</td>
<td></td>
<td>TAP Portugal</td>
<td>TP</td>
<td>star</td>
<td>1946</td>
<td>71</td>
<td>11.5</td>
</tr>
<tr>
<td>Finland</td>
<td>EU</td>
<td>35</td>
<td>34</td>
<td></td>
<td>Finn air</td>
<td>AY</td>
<td>one world</td>
<td>1968</td>
<td>68</td>
<td>8.4</td>
</tr>
<tr>
<td>Austria</td>
<td>EU</td>
<td>36</td>
<td>32</td>
<td></td>
<td>Austrian</td>
<td>OS</td>
<td>star</td>
<td>1958</td>
<td>80</td>
<td>14.3</td>
</tr>
<tr>
<td>Russian Federation</td>
<td>EU</td>
<td>11</td>
<td>9</td>
<td></td>
<td>Aeroflot Russian airlines</td>
<td>SU</td>
<td>sky team</td>
<td>1923</td>
<td>123</td>
<td>5.5</td>
</tr>
<tr>
<td>Qatar</td>
<td>EU</td>
<td>19</td>
<td>20</td>
<td></td>
<td>Qatar Airways</td>
<td>QR</td>
<td>N/A</td>
<td>1994</td>
<td>111</td>
<td>5.1</td>
</tr>
<tr>
<td>Saudi Arabia</td>
<td>EU</td>
<td>27</td>
<td>27</td>
<td></td>
<td>Saudi Arabian Airlines</td>
<td>SV</td>
<td>Sky team</td>
<td>1947</td>
<td>163</td>
<td>10.3</td>
</tr>
<tr>
<td>Israel</td>
<td>EU</td>
<td>34</td>
<td>36</td>
<td></td>
<td>El Al</td>
<td>LY</td>
<td></td>
<td>1949</td>
<td>40</td>
<td>13.4</td>
</tr>
</tbody>
</table>

33 Countries and 39 Airlines

Notes: PAX (passenger), NA: Not applicable