

COMPARATIVE EFFICIENCY ANALYSIS OF MAJOR AIRLINE IN THE UNITED

STATES BY BILATERAL DATA ENVELOPMENT ANALYSIS:

BEFORE AND AFTER THE MERGE

By

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To the Faculty of Washington State University:

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Abstract

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This paper studies the effects of mergers on the efficiency of airlines with fuel cost, ASM (available seats mileage) per employee, revenue passenger miles and load factor. The Bilateral DEA model is conducted to separate each airline into two periods: before and after alliance. This paper also introduces auxiliary validation to compare two periods of the trend in the conclusion and analysis part. The result shows that there is a significant loss in efficiency between the two periods for all airlines selected except Alaska airlines.

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SECTION ONE

INTRODUCTION

According to industry statistics from the International Air Transport Association (IATA), the global passenger has increased by 735 million and the cargo traffic of commercial airlines increased 6.4 million tons from 2008 to 2014 (Xu et al. 2017). Given this global background, the research of airline economic research is increasingly more valuable. In recent years, the fierce competition among airlines has led to the phenomenon of merger (Vieira et al. 2019). With the deregulation and liberalization of the aviation industry, the number of airline alliances is increasing worldwide. For instance, the world's largest airlines, including American Airlines, Southwest Airlines, Delta Airlines and China Southern Airlines, all experienced merges in the 20th century. (Yan et al. 2016)

Since deregulation in 1978, the U.S. airline industry has seen two major waves of airline consolidation. During the first wave of consolidations and bankruptcies¹, the number of major domestic airlines decreased from 23 to 8 (Bailey and Liu, 1995). During the same period, the Hub-and-Spoke services became the standard for mainstream operations, while Point-to-Point services became rare, contrary to the predictions of most researchers before deregulation (Bailey and Liu, 1995). The second wave of mergers begins in 2005. During this period, the major airlines² reduced from seven³ to five, the remaining five major airlines are American Airlines (AA), Delta Airlines (DL), United Airlines (UA), Southwest airlines (SW) and Alaska Airlines (ALA). These five airlines are chosen for further discussion in this paper from the year 1995 to 2018.

These airlines' revenue change further promoting research into airline operating efficiency. Caves et al. (1984) use Trans log Cost Function to study the efficiency of 15 U.S airlines from

¹ The first wave is the period from deregulation to the 1990s.

² The major airlines defined as airlines who carry at least 5% of the domestic passengers.

³ The old seven major airlines are: Northwest Airlines (NW), Continental Airlines (CO), American Airlines (AA), Delta Airlines (DL), United Airlines (UA), Southwest airlines (SW) Alaska Airlines. (AA)

1970 to 1981, the limitation is that it ignored the impact of airline density on the cost. The density of air traffic is an important element which affects operating costs, and smaller airlines usually have higher prices. Bauer et al. (1990) use Total Factor Productivity to study the efficiency of 12 U.S airlines between 1970 and 1981. The limitation of the study is that the result from the TFP⁴ (Total Factor Productivity) model has been negative, thus from the model itself it is hard to explain efficiency. Good et al. (1993) use the Cobb-Douglas function to observe the efficiency of 12 European and U.S airlines from the period 1976 to 1986. The limitation is that comparing European airline and U.S airlines is not fair enough because the liberation in the European airline resulted in potential efficiency gains.

Under the limitation from the models above, DEA (Data Envelope Analysis) shows its unique advantages. Schefczyk et al. (1993) analyze the 15 international airlines from 1989 to 1992 using the standard DEA model. The virtue of the standard DEA is that it chooses efficient resource acquisition, marketing, sales activities and operational performance as factors of high profitability. Among which operational performance is considered as a key factor. Based on standard DEA, Distexhe et al. (1994) use the Malmquist Productivity index, which mentions three sources of potential airline growth: route network characteristics, efficiency change, and technological progress.

Scheraga (2004) uses DEA and Tobit analysis to study whether the high performance of efficiency is related to financial mobility. This article discusses the events of September 11 and the weak U.S. economy had a ripple effect on other countries. Clearly, the airline industry has both operational and financial problems. But it is crucial to investigate whether September 11 really represents a discrete industry disruption, examining the structural drivers of the airline operating efficiency in the run-up to September 11, as well as the state of airline finances. This survey was conducted to understand better that the airline strategic needs to be a comprehensive process that

⁴ $TFP=y-F$, where y is observed output, F is an aggregate measure of observed input usage. TFP less than zero implicate an inefficiency.

reflects the business efficiency and financial flexibility factor. The result shows that relative operational efficiency does not necessarily indicate superior financial mobility.

Choi (2017) examines the productivity and efficiency of 14 U.S. airlines between 2006 and 2015, and measures changes in operational efficiency at each airline to conclude a tailored strategic plan. Besides, he analyzes the long-term impact of mergers and acquisitions among American airlines by combining the bootstrap efficiency score and the RTS (return to scale) perspective. The main findings of the study are: firstly, under the variable gain of scale (VRS) hypothesis, the efficiency analysis of the airline group shows that network legacy carriers (NLC) are the most efficient, followed by ultra-low-cost carriers (ULCC) and low-cost carriers (LCC). Secondly, the performance comparison study of the merges of the three airlines shows that the economic return on scale and efficiency level could have positive or negative effects. This shows that new service innovation is still needed to improve airline efficiency.

Liu (2017) uses the multi-period Network DEA model and the weighted Malmquist productivity index (MPI) to measure the efficiency changes of ten east Asian airlines from 2011 to 2014. One conclusion is that none of the sampled airport companies has achieved efficiency over the past four years because neither of the two sub-processes⁵ is efficient.

Min et al. (2016) use DEA model to test the technology efficiency of three main alliance (SkyTeam, Oneworld, Star Alliance) and compare the efficiency with a non-alliance group. Results indicate although the sharing of resources and customer base can be cost saving, the airline alliance does not necessarily improve operational efficiency.

⁵ aeronautical service and commercial service

Table 1. Relevant Literature

| Author | Year | Method | Result |
|------------------|------|--------------------------------|--|
| Caves et al. | 1984 | Trans log Cost Function | Smaller airlines normally have higher costs. |
| Bauer et al. | 1990 | Total Factor Productivity | Negative TFP is hard to explain efficiency |
| Good et al. | 1993 | Cobb-Douglas function | Inputs can be decreased without altering output. |
| Schefczyk et al. | 1993 | Standard DEA | Defines an input–output model characterized by two outputs and three inputs. |
| Scheraga | 2004 | DEA and Tobit analysis | High performance does not imply high financial mobility |
| Liu | 2017 | multi-period Network DEA & MPI | All sampled airport does not achieve efficiency |
| Choi | 2017 | output-oriented DEA | Merger and Alliance in the US airlines have been a mixture of successes and failures |
| Min et al. | 2016 | standard DEA | Alliance do not improve efficiency |

Table 1 summarizes the relevant literature previously discussed. This study follows Choi (2017) and Min et al. (2015). Instead of study four major alliances, I focus on five major airlines in the U.S and how the merging affects their efficiency. Notice that the alliance of airlines means airline exists separately but work within a partnership, sharing customers and other resources.

Airline merges, however, means two airlines combined as one. In this paper, I study how merging changes the efficiency of airlines, rather than the alliances. Other main differences of this study include using Bilateral-DEA instead of output-oriented DEA⁶. And change the assumption of various returns on the scale into constant return on the scale. My result agrees with Choi's study that mergers have a mixed effect on airlines. An improvement compared with Min's research is that, instead of comparing alliances against the non-alliance group, this study added a model to measure the difference before and after the merge to improve the accuracy of analysis. These changes in this paper improved the accuracy of the result. I use the auxiliary verification method to compare the efficiency score of each airline with the control group (Frontier airlines), and the result obtained from auxiliary verification is compared with the result from Bilateral DEA to verify the accuracy of this research.

⁶ Bilateral DEA is only affected by constant/various ROS, not by input/output orientation.

SECTION TWO

CONCEPTUAL FRAMEWORK

Decision Making Units (DMU)

DMU is the object of efficiency evaluation, which can be understood as an entity that converts a certain "input" into a certain "output" (Yang et al. 2013). Each DMU transforms a certain number of production factors into products in the production process to achieve its own decision-making goals, so they all show certain economic significance.

The DMU used in this paper refers to homogeneous individuals, that is, DMU has the following characteristics:

- i. It considers the same goal
- ii. It considers the same external environment
- iii. It considers the same input and output targets

Production Possibility Set (PPS)

Let X and Y be the inputs and output vectors of a certain DMU in its production activities, then (X, Y) can be used to represent the entire production activities of this DMU. Consider n DMU units, each unit DMU_j ($j=1, 2, 3, \dots, n$) has m inputs X_{ij} ($i=1, 2, 3, \dots, m$) and s outputs Y_{rj} ($r=1, 2, 3, \dots, s$).

Definition 1: This set $T = \{(X, Y) | \text{output } Y \text{ can be produced with input } X\}$ is called the production possible set consisting of all possible production activities.

According to the study of Banker et al. (1986), the production set needs to meet four postulates:

Postulates 1 (convexity): for $(x, y) \in T, (x', y') \in T$ and $\mu \in [0, 1]$, we have $\mu(x, y) + (1 - \mu)(x', y') \in T$.

Postulates 2 (monotonicity): if $(x, y) \in T, k \geq 0$, then $k(x, y) = (kx, ky) \in T$.

Postulates 3 (inclusion): define $(x, y) \in T$, if $x' \geq x$, then $(x', y) \in T$; if $y' \leq y$, then $(x, y') \in T$.

Postulates 4 (minimum extrapolation): Production possible set T is the intersection of all sets satisfying the above postulates 1- postulates 3.

Postulates 1 indicates that the production possibilities set T is a convex set. Postulates 2 shows that if we produce with k times of the original input, we can get k times of the original output. Postulates 3 shows it is always possible to increase or decrease output on the basis of the original production activity. Postulates 4 indicates that set T is the intersection of all requirements from Postulates 1 to 3.

Production Frontier

An important contribution of DEA is to provide a practical production frontier, which means that the frontier is connected by the effective production DMU units.

In DEA theory, determine the validity of a DMU is to judge whether the DMU falls on the production frontier of production possibility set.

Efficiency

In DEA models, efficiency usually includes technical efficiency, scale efficiency and allocative efficiency.

Technical efficiency refers to the ratio of actual output to ideal output on the premise of keeping the input of the decision-making unit unchanged. Technical efficiency reflects the potential of the DMU to achieve the maximum output at a given input situation. In general, technical efficiency is between 0 and 1. If the technical efficiency value is equal to 1, it indicates that DMU maximizes output at the current input level and is technically effective. If the technical

efficiency is less than 1, it indicates that there is still a gap between the actual output of DMU and the ideal output, and it is not located on the production frontier.

Scale efficiency is defined based on CCR efficiency and BCC efficiency. Cooper et al (2000) defined CCR efficiency value as the global technical efficiency, BCC efficiency value as pure technical efficiency, the ratio between the two is called the scale efficiency, namely the DMU in size under the same technical efficiency and scale compensation under the variable of the ratio of technical efficiency. Similarly, when the scale efficiency is equal to 1, indicating that the DMU is valid, while the scale efficiency value is less than 1, indicating that the DMU is invalid.

Allocative efficiency refers to the ratio of the overall efficiency and technical efficiency of the DMU, under the assumption of keeping the output of the DMU unchanged (Hartman et al. 2001). The total efficiency is defined as the ratio of the minimum cost of the DMU to the actual cost. In calculating the overall efficiency, price information for all input variables is considered. The closer the overall efficiency is to 1, the closer the operation cost of the DMU is to the ideal state. When the allocative efficiency is equal to 1, the allocation of the DMU is effective.

SECTION THREE

SELECTION OF MODEL

Brief History and Virtue of DEA

Data envelopment analysis (DEA) is a non-parametric evaluation method for relative efficiency proposed by American operations research scientist Charnes, Cooper and Rhodes (CCR) in 1978. It is mainly applicable to the relative efficiency evaluation of multiple decision-making units with the same type of input and output. The basic idea of its evaluation is to take each evaluated object as a DMU and construct all DMU into evaluated DMUs. By analyzing the input-output ratio of each DMU, the effective production frontier is determined. Then, according to the distance between each DMU and the effective production frontier, one can determine whether the evaluated object is DEA effective or not.

An important contribution of DEA is to use the possibility of frontier of actual production. In benchmarking, the efficient Decision-Making Units defined by DEA may not necessarily form the "production frontier" but lead to the "best practice frontier" (Cook, et al. 2014). DEA is referred to as "equilibrium benchmark" by Sherman and Zhu (2013). Under this method, the reference for measuring efficiency changes from the theoretical production possibility boundary to the practical optimal production boundary. DEA introduced an important concept, which is a linear combination of the input, output, and weight, form virtual input and output. Each DEA based on the DMU must result in its relative efficiency; that is, each efficiency is compared to the effective DMU. Therefore, DEA can estimate the relative efficiency between all involved DMU, which is an important attribute of an organization.

Some other advantages of DEA are:

- First, DEA method can be used to evaluate the production (operation) performance of decision-making units with multiple inputs and multiple outputs. DEA method does not need to specify the production function shape of input and output, so it can evaluate the

efficiency of decision-making units with complex production relationships. It helps reveal relationships hidden by other methods; when using DEA, the relationship within elements were conducted.

- Second, it has the characteristic of unit invariance; that is, the result of DMU measured by DEA is not affected by the unit selected for input-output data. As long as the unit of input and output data is unified, the change of any unit of input and output data will not affect the efficiency result. It can simultaneously process proportional data and non-proportional data, that is, input and output data can simultaneously use proportional data and non-proportional data, as long as the data is able to reflect the decision-making unit input or output surface of the main indicators can be.
- Third, in the DEA model, the weight is decided by mathematical programming; we do not need to set the input and output of weight, so is not influenced by subjective factors. The prior enactment weight method, such as the expert evaluation method, is easily affected by subjective factors.
- Fourth, DEA can carry out a comparative analysis between the target value and actual value, sensitivity analysis and efficiency analysis. It can further understand the use of resources in decision-making units and provide a reference for managers' business decisions. Therefore, all random disturbances are considered efficiency factors. Sources of inefficiency can be analyzed and quantified for each evaluation unit. Assume that the efficiency calculated through DEA is less than 1, one can determine how to improve efficiency by looking at the relationship between DMU. For example, the input of hospital efficiency includes the number of doctors and nurses, etc. When the efficiency is less than 1, it can be considered to reduce the input, that is, to reduce the number of medical staff to improve efficiency.

CCR

Banker et al. (1986) changed the basic assumptions of CCR. The basic assumption of CCR is that returns on the scale are constant, while the basic assumption of BCC is that returns on the scale are variable. The weakness of these two models is that there are many effective units, i.e., the single element with an efficiency rating of 1, and these effective units cannot be further evaluated.

Super-SBM

The super-efficiency model proposed by Anersen et al. (1993) can be used to rank efficient units of DEA again. The specific steps are as follows:

- I. Efficiency calculated by CCR model (E)
- II. Super-efficiency efficiency (SE) calculated by super-efficiency model.

| Stores | SBM score | Super-SBM |
|--------|-----------|-----------|
| A | 0.8 | - |
| B | 0.6 | - |
| C | 1 | 1.125 |
| D | 1 | 1.25 |
| E | 1 | 1.5 |
| F | 0.9 | - |

Suppose there are six stores, labeled A-F. The efficiency value was 0.8, 0.6, 1, 1, 1, 0.9 respectively. At this point the production possibilities frontier is a line connected by C, D, E. After Super-SBM is run, it is concluded that the efficiency of C, D and E is 1.125, 1.25 and 1.5 respectively (note that the efficiency under general DEA is less than or equal to 1, but the efficiency under super-SBM is generally greater than 1). At this point, the distance from point E to the new production possibility boundary, EG (let G be the intersection point between point E and the line parallel to

the X-axis and PPF), the distance from point E to point D, ED, and the distance from point E to point C, EC, is the value of super-SBM. After running Super-SBM, one can screen out which of multiple DMU that equals to 1 is the most effective. On the basis of CCR, the efficiency of multiple points with the efficiency of 1 is measured by Super-SBM, but it cannot be directly used to compare the efficiency of airlines before and after the merger.

Categorical DEA

Categorical DEA: Refers to the need to consider the differences in the environment and attributes of different groups of DMU when evaluating the efficiency of DMU. Therefore, it is necessary to divide the DMU into several groups with the same attribute, that is, to divide the evaluated DEA into several layers and evaluate their efficiency. Suppose some supermarkets have numbers of stores, one need to consider all the stores of the different geographical position, economic development level is different, the competitive environment is different, this time will be applied Categorical DEA to classify all the stores.

Class i: internal efficiency evaluation between DMU (using CCR/BCC/SBM)

Class ii: evaluation with reference to class i and class ii (combining I and ii into a new data set and then using the method of calculating class i)

Class iii: refer to class i, ii and iii. (calculate the efficiency value of all DMU)

Categorical DEA solves the short come of Super-SBM that it cannot measure efficiency in different situations. However, due to the particularity of airline companies, it is difficult to divide flights into regional categories, because flights are interconnected.

Bilateral DEA

The general DEA based on common follows the same possible productive front. However, different groups of DMU are often based on different frontiers, so these groups are called different systems, and the convexity assumption of traditional DEA is followed within the groups. At this level, Bilateral DEA is the most suitable research method for the purpose of this paper. By Bilateral

DEA, airlines can be divided into two groups: before and after the merger. Here, it is assumed that before the merger, airlines have a different customer and technological resources. After the merger, because the two companies merged into one, and resources to achieve the sharing, therefore can be divided into the second group.

SECTION FOUR

SELECTION OF INDEX

Selection of DMU

American Airlines (AA), one of the founding members of the One World family, is the world's largest airline. Jointly affiliated with American Eagle Airlines and the United States, American Airlines has more than 260 navigable cities-including 150 cities in the United States and cities in 40 countries.

On December 9, 2013, American Airlines parent company AMR and American Airlines Group officially announced that the combined transaction between the two companies had been completed, thereby creating the world's largest aviation operator.

Delta Airlines⁷ (DL): Delta Airlines has a long history started in 1928. In 2008, Delta Air Lines merged with Northwest Airlines to form Delta Air Lines. Delta Air Lines is the third largest airline in the United States and is headquartered in Atlanta.

United Airlines (UA): United Airlines is a major airline in the U.S., as well as the third largest airline in the world. UA merged with Continental Airlines in 2010.

Southwest airlines (SW): Southwest Airline is the largest low-cost airline in the world as well as a major airline in the U.S. There are two mergers experience in the history for SW, one with Morris Airlines in 1993, and another is with AirTran Airways in 2011.

Alaska Airlines (ALA): Alaska is also an important airline in the U.S. with respect to fleet size, the number of destinations and scheduled capacity. Notice that ALA is not a member of Star Alliance.

Alaska Airline is the fifth largest airline in the United States when considered by scheduled capacity, the number of destinations served and fleet size. Alaska operates a vast network of

⁷ History of DL from Delta Flight Museum. www.deltamuseum.org. Retrieved. Oct.2 2019

domestic routes with its regional partners. Alaska Airlines is not a member of three major airline alliances⁸. However, it has signed a code-sharing agreement with 17 airlines, including SkyTeam, One World, and Star Alliance member airlines. Regional service is operated by sister airline Horizon Air and independent carrier SkyWest Airlines.

Selection of input and output units

Input 1 Fuel Cost: Airlines have a unique operating structure, in which aviation fuel accounts for about 30%-40% of operating expenditure (Swidan et al. 2019). Any fluctuation in the price of aviation fuel may cause a disturbing financial impact of airlines, so it is necessary to take fuel cost as the research index in terms of the ratio of total cost to total cost and the impact on airlines. Chiou and Chen (2006) choose fuel cost as one of the input units for DEA model to study one Taiwanese airline in 15 routes. Barbot et al. (2008) choose Fuel consumed as an input unit to evaluate the efficiency of 49 international airlines. Lozano and Gutierrez (2011) also choose fuel costs as one of the input units to study the efficiency of 17 European airlines.

Input 2 ASM per Employee: ASM, a common industry measure of airline output, refers to flying one mile in an airplane seat, occupied or not. A plane with 100 passenger seats can travel 100 miles and generate 10,000 seat miles. ASM per employee is a more accurate measure of the number of employees on flights because it excludes the impact of different wage levels, and instead measures the number of miles traveled and the number of employees. Zhu (2011) choose CASM, salary per ASM, wages per ASM, benefits per ASM, fuel expense per ASM to analysis 21 international airlines. Bhadra (2009) uses ASM as an input when analysis 13 U.S. airline.

Output 1 Revenue Passenger Miles: Revenue passenger mileage is the basic amount of "production" created by airlines. The total passenger load factor could be determined by comparing revenue passenger miles with available seat miles on an airline system. These measures can be

⁸ Star Alliance, one world, and SkyTeam are the world's 3 major airline alliances

further used to measure unit revenue and unit cost. Wang et al. (2011) study for 30 U.S. airlines by using RPM as an output.

Output 2 Load Factor: ASM's revenue passenger miles (RPMS) are expressed as ASM percentages on a given flight or system. The load factor represents the percentage of actually consumed airline output. The calculation process includes dividing RPMS by ASM. Zhu (2011) choose Load Factor as an output in the study mentioned in fuel cost section.

The following table 2 represents merge history of Southwest Airlines, American Airlines, Delta Airlines and Alaska Airlines.

Table 2 Airline Merger Status from 1993 to 2014

| Merging airlines | Merged entity | Year |
|-------------------------|----------------------|-------------|
| Morris Airlines /SW | SW | 1993 |
| Reno Air/AA | AA | 1999 |
| Atlantic Southeast/DL | DL | 1999 |
| Comair/DL | DL | 1999 |
| TWA/AA | AA | 2001 |
| Northwest Airlines/DL | DL | 2009 |
| Continental Airlines/UA | UA | 2010 |
| AirTran Airways/SW | SW | 2011 |

| | | |
|--------------------|-----|------|
| Virgin America/ALA | ALA | 2014 |
|--------------------|-----|------|

SECTION FIVE

MATHEMATICAL FUNCTION

DEA Model set-up

Objective Function: This is the objective function that maximizes efficiency E, which is calculated by using the sum of input item weight⁹ combination divided by output item weight combination.

$$\text{Max } E = \frac{\sum_{j=1}^n Y_j u_j}{\sum_{i=1}^m X_i v_i}$$

Constraint: These are constraints of the objective function; the first constraint assumes that normally efficiency will not be greater than 1. The second and third constraint states that the relative efficiency reduction caused by a reduction in the value of output or input unit is a positive related relationship (reduction of efficiency will not lead to an increase of input/output).

$$\text{s.t. } u_j \geq 0, j=1,2, \dots, n$$

$$v_i \geq 0, i=1,2, \dots, n$$

Table 3. Meaning of Variables

| | |
|---|--|
| E | Efficiency. In the formula, E maximization is taken as the objective formula to find the most favorable input item weight combination and output item weight combination to maximize E |
| m | m inputs, equal to 2 (Fuel Cost, ASM per employee) |
| n | n outputs, equal to 2 (Revenue Passenger Miles and Payload) |

⁹ DEA Slover first determines the connection between the data and the efficiency by analysis the trend of the data, then uses the formula weight input= $x_1v_1+x_2v_2$, and output weight= $y_1u_1+y_2u_2$. The efficiency is obtained by weight output/weight input. The systems will repeatedly calculate for combinations of v_j and u_i until the efficiency for each DMU reach a maximum

| | |
|-------|--|
| u_j | The coefficient of the J_{th} output, u_j is used to measure the relative efficiency reduction caused by a reduction in the value of output by one unit. |
| v_i | The coefficient of the i_{th} input, v_i is used to measure the relative efficiency reduction caused by the reduction of the input value by one unit. |
| Y_j | The j_{th} output |
| X_i | The i_{th} input |

Hypothesis

The null hypothesis of this paper is:

H₀: airline mergers have no significant impact on their efficiency

The alternative hypothesis is:

H₁: there is a significant difference before and after mergers

Reject Region: reject null hypothesis when a significant level is less than 0.1 (10%)

Auxiliary validation

The difference-in-difference model is mainly used to evaluate policy effects in sociology. The principle is based on a counterfactual framework to evaluate the change in observed factor y when the policy occurs and when it does not. If an exogenous policy shock divides the sample into two groups -- the Treat group subject to policy intervention and the Control group subject to no policy intervention, and there is no significant difference in y between the Treat group and the Control group before and after the policy impact, then we can regard the change in y of the Control group before and after the policy impact as the condition when the Treat group is not subject to

policy impact (a counterfactual result). By comparing the change in Treat group y (D1) with the change in Control group y (D2), we can obtain the actual effect of policy impact (DID= $d1-d2$).

Since external evidence changes are not covered in this article, the DID model is not applicable. However, based on the basic ideas and assumptions of DID model, a control group was selected for each airline to test the significance of the impact of the merger.

There is a small number of unconsolidated airlines. For some unconsolidated airlines, they do not have complete operating data (1995-2007). Only Frontier Airline¹⁰ (FRT) satisfies the unconsolidated and complete data set. Therefore, Frontier and five airlines were selected for comparison.

The process of Auxiliary validation is: (Take DL and FRT for example)

1. Use Bilateral DEA model in DEA – Solver to calculation efficiency. For DL a recent merger in 2009, so 1995-2009 for the first group, 2010-2017 as the second group. Then get the value of efficiency.

2. Select FRT as a control group. Reference is made to the grouping of DL, namely, 1995-2009 is the first group and 2009-2017 is the second group. Get the efficiency per year.

3. Compare the efficiency values of DL and FRT.

Table 4 shows details about five auxiliary validation groups, Frontier is the control group for all airlines.

Table 4. Auxiliary Validation Groups

¹⁰ Based on data from airlinedataproject.com

| Airline | Latest merge year ¹¹ | Control group | Auxiliary validation Group |
|-------------------------|---------------------------------|---------------|----------------------------|
| American Airlines (AA) | 2001 | Frontier | 1 |
| Delta Airlines (DL) | 2009 | Frontier | 2 |
| United Airlines (UN) | 2010 | Frontier | 3 |
| Southwest Airlines (SW) | 2011 | Frontier | 4 |
| Alaska Airlines (AL) | 2014 | Frontier | 5 |

SECTION SIX

¹¹ Refer to table 2

DATA & RESULT

All the data are collected from the Airline Data Project and Annual reports from observation airlines. All the input and output parameters correspond to domestic flights.

By using DEA Slover Pro 5.0 in Excel, the efficiency is calculated with two input units and two output units.

The data below in table 5 is used to analyze overall efficiency trend in Figure 6. Most airlines have half the efficiency exceeding 1. The most efficient point appears in SW, the year is 1995.

Table 6 is the result of significant level, which includes the name of airlines, hypothesis, rejection region, significant level and description of performance. The significant level is the statistic importance of this research.

Table 5. Efficiency Score from DEA Solver

| Year | AA | DL | UN | SW | AL |
|------|----------|----------|----------|----------|----------|
| 1995 | 1.221393 | 1.422801 | 1.326005 | 2.312139 | 1.61454 |
| 1996 | 1.133126 | 1.306518 | 1.181893 | 2.061016 | 1.487059 |
| 1997 | 1.148621 | 1.313113 | 1.190017 | 2.07802 | 1.512157 |
| 1998 | 1.300233 | 1.464766 | 1.307377 | 2.510365 | 1.709465 |
| 1999 | 1.259589 | 1.473979 | 1.321113 | 2.34149 | 1.554694 |
| 2000 | 1.03135 | 1.347254 | 1.139755 | 1.765012 | 1.299588 |
| 2001 | 1.001471 | 1.36222 | 1.110619 | 1.753157 | 1.361702 |
| 2002 | 1.051818 | 1.383503 | 1.252556 | 1.746831 | 1.398842 |
| 2003 | 0.856946 | 1.379752 | 1.217761 | 1.698418 | 1.318755 |
| 2004 | 0.703726 | 1.135333 | 1.052931 | 1.584641 | 1.133705 |
| 2005 | 0.643629 | 0.812494 | 0.802558 | 1.392415 | 1.010806 |
| 2006 | 0.630161 | 0.763757 | 0.734023 | 1.15144 | 0.585748 |

| | | | | | |
|------|----------|----------|----------|----------|----------|
| 2007 | 0.615814 | 0.822143 | 0.73583 | 1.069817 | 0.579453 |
| 2008 | 0.565343 | 0.637899 | 0.585522 | 0.690216 | 0.512288 |
| 2009 | 0.62642 | 0.538024 | 1.095151 | 1.028902 | 1.05763 |
| 2010 | 0.602537 | 0.614761 | 0.550466 | 0.765264 | 0.627973 |
| 2011 | 0.564505 | 0.60231 | 0.512302 | 1.036439 | 0.544134 |
| 2012 | 0.546428 | 0.597183 | 0.601305 | 1.121629 | 0.544394 |
| 2013 | 0.514419 | 0.58962 | 0.61693 | 1.107644 | 0.544471 |
| 2014 | 0.538459 | 0.571735 | 0.608559 | 1.135687 | 1.052706 |
| 2015 | 1.080875 | 0.687548 | 0.690155 | 1.185164 | 1.143489 |
| 2016 | 1.086085 | 1.019028 | 0.781653 | 1.222942 | 1.388925 |
| 2017 | 1.085664 | 1.041228 | 0.711927 | 1.254428 | 1.215389 |
| 2018 | 1.087448 | 1.06232 | 0.641638 | 1.260092 | 1.297532 |

Table 6. Significant level from DEA Solver (Group 1 is before merge and Group 2 is after merge)

| Airline | Null Hypothesis | Result | Significant level | Performance |
|-----------|--|-------------|-------------------|-----------------------------|
| AA | the two groups have the same distribution of efficiency score. | Reject Null | 0.10882% | Group1 outperforms Group 2. |
| DL | the two groups have the same distribution of efficiency score. | Reject Null | 0.08451% | Group1 outperforms Group 2. |

| | | | | |
|-----------|--|--------------------|-----------|-----------------------------|
| UN | the two groups have the same distribution of efficiency score. | Reject Null | 0.048616% | Group1 outperforms Group 2. |
| SW | the two groups have the same distribution of efficiency score. | Reject Null | 7.57526% | Group1 outperforms Group 2. |
| AL | the two groups have the same distribution of efficiency score. | Do not reject null | 10% | - |

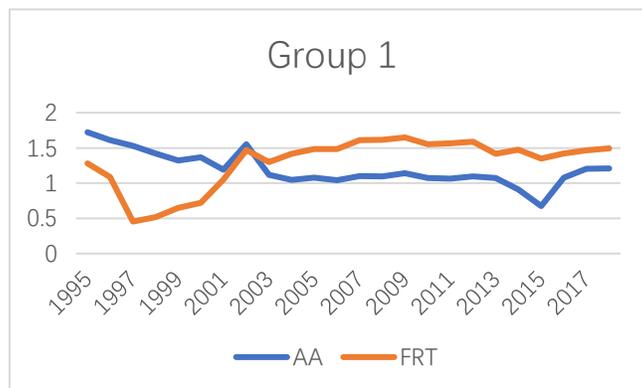


Figure 1. Auxiliary validation Group 1: American Airline & Frontier Airline

Figure 1 Analysis: The latest merger for American Airlines is in 2001. Thus, group 1 is 1995-2001; group 2 is 2002-2017. Reject the null of no difference between the two group and conclude that group 2 is outperformed by group 1. Based on this graph, the treatment group FRT

has an efficiency score above AA after year 2001, so the result of auxiliary validation is compliance with the result from DEA Solver.

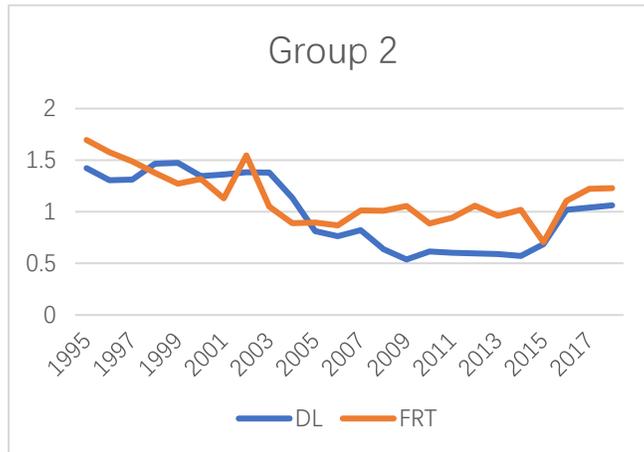


Figure 2. Auxiliary validation Group 2: Delta Airline & Frontier Airline

Figure 2 Analysis: The latest merger for Delta Airlines is in 2009. Thus, group 1 is 1995-2009, group 2 is 2010-2017. Reject the null of no difference between the two group and conclude that group 2 is outperformed by group 1. Based on this graph, the treatment group FRT has an efficiency score above DL from 2005 to 2015, this period partly agrees with the result from DEA Solver. The efficiency of DL shows an upward trend after 2015.

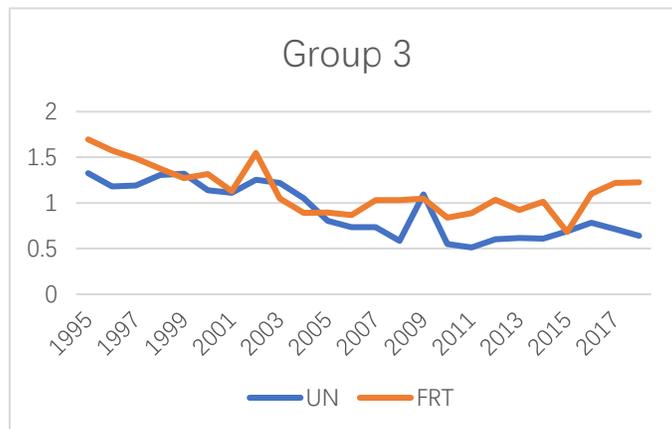


Figure 3. Auxiliary validation Group 3: United Airline & Frontier Airline

The latest merger for United Airlines is in 2010. Thus, group 1 is 1995-2010 and group 2 is 2011-2017. Reject the null of no difference between the two group and conclude that group 2 is outperformed by group 1. Based on this graph, the treatment group FRT has an efficiency score above UA from 2005 to 2015. This period partly agrees with the result from DEA Solver. The efficiency of UA shows an upward trend after 2015.

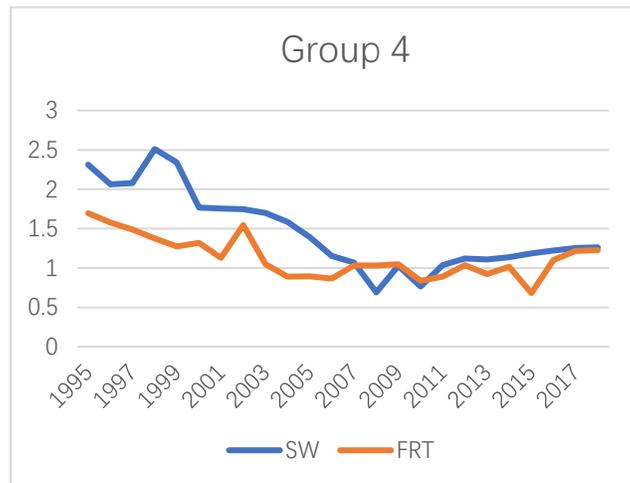


Figure 4. Auxiliary validation Group 4: Southwest Airline & Frontier Airline

The latest merger for Southwest Airlines is in 2011. Thus, group 1 is 1995-2011 and group 2 is 2012-2017. Reject the null of no difference between the two groups and conclude that group 2 is outperformed by group 1. Based on this graph, the treatment group FRT has an efficiency score under UA from 2009 to 2017, this period partly disagrees with the result from DEA Solver, which means the efficiency change of SW may not determine by a merger in year 2011.

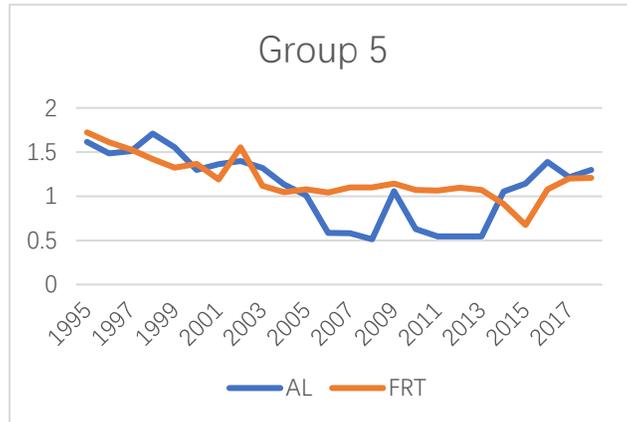


Figure 5. Auxiliary validation Group 5: Alaska Airline & Frontier Airline

The latest merger for Alaska Airlines is in 2014. Thus, group 1 is 1995-2014 and group 2 is 2015-2017. Do not reject the null of no difference between the two groups and conclude that group 2 is outperformed by group 1. Based on this graph, the treatment group FRT that has an efficiency score has a mixed trend with AL group, so it is hard to say which group is outperformance another.

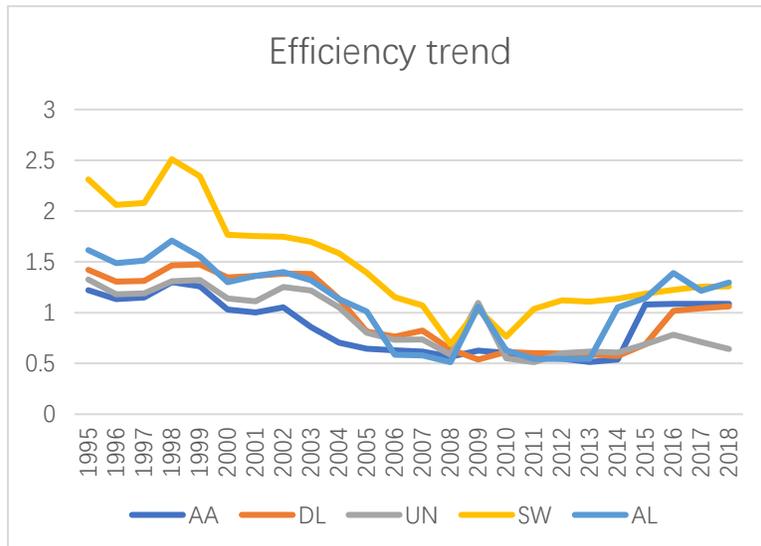


Figure 6. Total Efficiency Trend

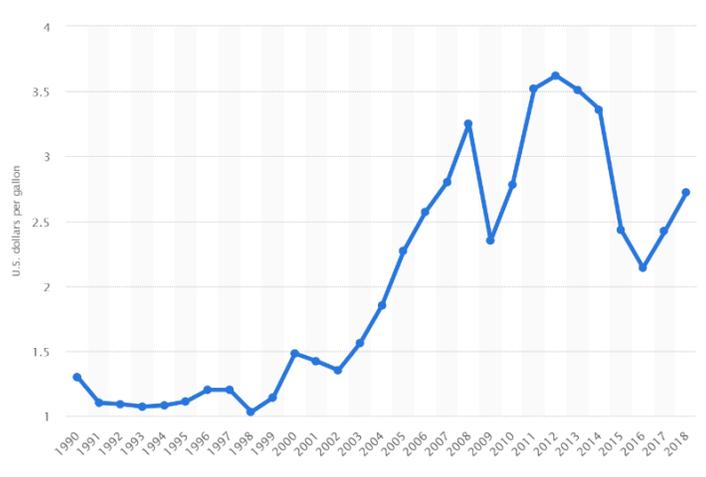


Figure 7¹². Fuel Price Trend

Figure 6 and 7 Analysis: Based on graph 6, the first thing to notice would be that an integrated drop period from 2000 to 2008. Combined with graph 7, the oil price from 1990 to 2018 has increased gradually and has a steep increase from 2004 to 2008, which perfectly matches the lowest period of efficiency. Notice that there is a drop of oil price from 2008 to 2010, deepest in 2009, which consistent with a small peak for SW and AL in 2009, so the oil price would be the main reason that all chosen airlines show a declining trend in efficiency since the input would increase along with oil prices.

More specifically, on September 14, 2005, delta airlines filed for bankruptcy, citing rising fuel prices. It went bankrupt in April 2007 after resisting a hostile takeover by American airlines. A specific example from AL could explain why the number of graduates fell from 2004 to 2008 and peaked in 2016. The 2004 accident prompted Alaska airlines to phase out the remaining 26 md-80s and train pilots to fly the new 737-800s because the new generation of Boeing 737s is more efficient and costs for fuel, maintenance and crew training are rising.

¹² Graph 3resource from www.statista.com. Retail price of regular gasoline in the United States from 1990 to 2018 (in U.S. dollars per gallon)

In addition, there is a specific example from AA's 2010 small peak. On July 20, 2011, American airlines announced an order for 460 narrow-body aircraft, including 260 airbus a320s. The order is to break the monopoly on airlines, Boeing has forced Boeing to join the redesigned 737 MAX. The sale includes most-favored-nation customer terms. At the same time, orders for new aircraft can increase revenue and load factors, thereby increasing efficiency.

Other possible explanations and future improvements may include alliance network, alliance membership, and employee allocation.

Alliance network: Complementary alliance refers to the situation where two air carriers connect their existing networks to establish a new complementary network to provide traffic to each other (Hsu et al. 2008). If there is large network overlap before the merger, the efficiency may not improve in the short term after the merger.

Alliance membership: alliance refers to the cooperation agreement reached between two or more airlines. Cooperation usually includes code-sharing, shared maintenance facilities, and operating equipment. Among the airlines selected in this article, many merged airlines belonged to the same alliance before the merger. For example, UA and Continental belonged to the Star Alliance, and Delta and NW belonged to the SkyTeam. In this case, the merger may not bring immediate efficiency improvements, which also partially explains why the merge does not improve efficiency.

Employee allocation: Another factor that may affect efficiency is whether resources are shared between internal departments of airline. Most airlines are composed of several departments, such as transportation control, information department, marketing department, flight service department, finance department and so on. However, the proportion of internal staffing on flights may not be optimal, and the proportion of staffing distribution varies from airline to airline, so poor staffing may also cause inefficiency (Li et al. 2018).

SECTION SEVEN

CONCLUSION

This paper makes some improvements on the basis of Choi (2017) and Min et al. (2015), and the results have both similarities and differences. The similarity is concluding that the merger does not increase efficiency. The difference is that this paper show that merger has no significant effect on some airlines, such as ALA.

In addition, auxiliary validation is added in this paper to verify the accuracy of the results. Most of the verification results are identical with significant level, while a few are inconsistent with them, which may be due to some assumptions in this paper (whether the airline is an alliance is not considered when comparing efficiency).

Future research can focus on the relationship between alliance and merger, or study how the networks between departments in an airline affects efficiency.

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