DETERMINATION OF THE RESPONSIBILITY OF DELAY IN THE CONTEXT OF AIRLINE BUSINESS MODEL: A CASE OF AMERICAN AIRLINES AND SOUTHWEST AIRLINES

DETERMINACIÓN DE LA RESPONSABILIDAD DEL RETRASO EN EL CONTEXTO DEL MODELO DE NEGOCIO DE LAS AEROLÍNEAS: UN CASO DE AMERICAN AIRLINES Y SOUTHWEST AIRLINES

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ABSTRACT

The main factor in the airline transport service being the reason for the choice is the place and time benefit it provides. Delays are negative situations that disrupt the time utility, reduce airlines' profits, cause congestion trouble and disrupt tariff plans. The first part of the study consists of information about delays and fundamental issues related to delays. In the second part, it has been tried to summarize the studies on the slot, which is directly related to the delays. In the last part, two airlines that adopted different business models, full-service carrier and low-cost carrier, were compared based on delay reasons. The study aims to determine the causes of delay and their predictive roles comparatively. We have used the multiple hierarchical regression model for this purpose. American Airlines and Southwest Airlines were selected as full-service carrier and low-cost carrier, respectively. We have determined that even though Southwest Airlines is a low-cost carrier, and more punctual than American Airlines, delays stemming from the carrier play a greater role in overall delays than American Airlines.

Keywords: Airline business model; total delay; delay reasons; full-service carrier; low-cost carrier; multiple hierarchical regression

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RESUMEN

El principal factor en el servicio de transporte aéreo que es la razón de la elección es el lugar y el beneficio de tiempo que proporciona. Los retrasos son situaciones negativas que perturban la utilidad del tiempo, reducen los beneficios de las aerolíneas, causan problemas de congestión e interrumpen los planes arancelarios. La primera parte del estudio consiste en información sobre retrasos y cuestiones fundamentales relacionadas con los retrasos. En la segunda parte, se ha tratado de resumir los estudios sobre la ranura, que está directamente relacionada con los retrasos. En la última parte, se compararon dos aerolíneas que adoptaron diferentes modelos de negocio, la compañía de servicios completos y la compañía de bajo costo, por razones de retraso. El objetivo del estudio es determinar las causas del retraso y sus funciones predictivas comparativamente. Hemos utilizado el modelo de regresión jerárquica múltiple para este propósito. American Airlines y Southwest Airlines fueron seleccionados como transportistas de servicio completo y de bajo costo, respectivamente. Hemos determinado que aunque Southwest Airlines es una compañía de bajo costo, y más puntual que American Airlines, los retrasos derivados de la compañía desempeñan un papel más importante en los retrasos generales que American Airlines.

Palabras clave: Modelo de negocio de la aerolínea; retraso total; razones de retraso; compañía de servicio completo; compañía de bajo costo; regresión jerárquica multiple.

INTRODUCTION

The number of passengers benefiting from air transport services has increased 2.5 times in the last 15 years before the Covid-19 global crisis. While 1.8 billion passengers benefited from air transportation services in 2004 (IATA, 2005), in 2019, approximately 12.5 million passengers were served with 128 thousand flights every day, and 4.5 billion passengers were served with a total of 46.8 million scheduled flights. (ATAG, 2020). The number and variety of aircraft in the fleets of airline companies is not a sufficient factor to meet the increasing demands of the sector. In addition, the situation of air traffic and the issue of slots are also important. A slot can be thought of as a key required to enter a locked market. The inability to provide sufficient capacity in response to the increasing demand causes loss of passengers and thus income. Airports Council International (ACI) has emphasized that congestion at the 100 largest airports may result in the loss of approximately 1.2 billion passengers or diverting them to secondary airports by 2030, if the necessary precautions are not taken, (ACI, 2018). Airline companies must comply with the slot rules assigned to them by an authorized coordinator. If these rules are not followed, both the on-time performance will decrease, and the related flight of the airline will be delayed. In this case, the airline operator also loses the slot right that it has taken from the airport on the other leg of the flight and must buy slots again. Low on-time performance value and delays as a result of not following the slot rules have the potential to lower the load factor depending on passenger types, needs, and expectations. For example, Turkish Airlines served 75.1 million passengers with load factor of 81.9% in 2018, while it served 74.2 million passengers with load factor of 81.6% in 2019 (Turkish Airlines, 2021). According to IATA data, while the load factor was 76% in 2006 (IATA, 2007), this figure was 82.6% in 2019 (IATA, 2020). In this context, the aim of the study is to determine the predictive role of delay reasons on total delays in the context of the airline business model.

LITERATURE REVIEW

Air traffic tends to grow from past to present, excluding global adversities such as financial crises, oil crisis, Covid-19, terrorism (Gelhausen et al., 2019). In the USA, traffic delays due to air traffic became a major problem, increasing significantly in the late 1990s (Brueckner J. K., 2002). However, due to the lack of parallel development in the matter of airport capacity, delays are an additional cost to airline companies. For this reason, airport congestion is a serious problem (Czerny, 2010).

The reason why many flights are delayed is the lack of balance between demand and capacity (Jacquillat & Odoni, 2015). Congestion, especially at major airports, leads to increased taxi time and emissions (Clewlow et al., 2012). In the US market, the planes that taxiing in order to take off, cause approximately 6 million metric tonnes of carbon dioxide emission, and nearly half of that emission occurs at the country's 20 most congested airports (Simaiakis et al., 2014). While Grether et al. (1979) proposed the auction method for capacity allocation to the Federal Aviation Administration (Grether et al., 1979), Rassenti et al. (1982), developed a computer-aided optimization model to increase the overall efficiency of this method developed by Grether et al. (Rassenti et al., 1982). Brueckner (2002) stated that for delay and therefore congestion, a fare schedule may be applied at peak hours, according to the level of airport congestion (Brueckner J. K., 2002). Although the expansion of airport capacity and the construction of new runways are considered as another potential solution to the congestion problem, such an investment project requires bearing the high costs (Brueckner J. K., 2005). There are two main approaches to congestion management: price-based and quantity-based (Brueckner J. K., 2009).

The analyzes conducted by Brueckner focus on two hypothetical airlines. The fees that the airline operators are willing to pay for the relevant slots are defined as p1 and p2, respectively. Price-based approaches are divided into two as differentiated wage regime and uniform price regime. According to the differentiated fee regime, large carriers must pay more than small carriers. The uniform price regime, unlike the differentiated fare regime, is not concerned with whether the carriers are large or small, the slot price is fixed regardless of the size of the airline. The uniform price regime is inefficient and cannot generate optimal flight volumes for carriers. However, when the asymmetry between the carriers disappears, that is, when p1 = p2, inefficiency disappears. Quantity-based approaches have been the subject of the analysis because the differentiated wage application is controversial, and the uniform price application is inefficient in case of asymmetry. The slot distribution regime, which is the first of the quantity-based approaches, has been found to be efficient as a result of the studies. These approaches are the slot distribution regime and the auction method, which is also the subject of other studies, and they are effective. Zografos et al. (2012) developed an optimization-based model that utilizes integer programming, aiming to minimize the difference between slot times requested by airlines and assigned to airlines, in line with EU/IATA rules (Zografos et al., 2012).

Using the slot data of Chania (CHQ), Rhodes (RHO), and Herakleio (HER) airports in the study, the authors' analyzes show that the proposed model has ample room to improve the efficiency of the current slot allocation result between 14% and 95%. However, this model can only be used at small airports. Mukherjee and Hansen (2007) used dynamic stochastic integer programming model in their study aimed at capacity utilization efficiency (Mukherjee & Hansen, 2007). Ribeiro et al. (2018) proposed a priority-based slot allocation model (PSAM) aimed at slot allocation optimization

(Ribeiro et al., 2018). As a result of the implementation of this proposed model at two Portuguese airports, Madeira and Porto, it has been observed that the slot allocation efficiency has improved. Pellegrini et al. (2017) proposed the SOSTA model, which is an integer linear programming model with the contribution of slot allocation at all European airports, aiming at the optimization of the slot allocation process (Pellegrini et al., 2017). Using real data in the model, the authors, who evaluated the demand during the peak days of 2013, stated that the model did not contribute greatly compared to the current slot allocation, but still worked more optimized than the current allocation.

METHODOLOGY

The research was conducted to determine the predictive role of delay reasons on total delays in the context of the airline business model. In the sample of the research, two different airline business models were chosen: Southwest Airlines as the low-cost carrier and American Airlines as the full-service carrier. The fleet size factor was considered in the selection of the airline company. Both airlines are major carriers of their own business model. The delay data for both airlines are taken from the website of the Bureau of Transportation Statistics, which is affiliated with the US Department of Transportation. Data were collected from June 2003 to December 2021. The months of March and April 2020 were not included in the analysis due to heavy cancellations rather than delays. All analyzes were made by means of IBM SPSS Statistics (trial version). For the purpose of the study, hierarchical regression analysis was performed. The purpose of using hierarchical regression is to test theoretical assumptions and to determine the degree to which variables entered later in the analysis account for variance in the criterion over and above that which is accounted for by variables entered earlier in the analysis (Petrocelli, 2003). Petrocelli (2013) stated that a major advantage of hierarchical regression is of course the ability to examine the significance of the incremental increases in R^2 when more than one predictor is of interest or a set of predictors that share some relevant commonalities are of interest (Petrocelli, 2013). The Bureau of Transportation Statistics explains the reasons for the delay as follows (Bureau of Transportation Statistics, 2021):

Air Carrier: The cause of the cancellation or delay was due to circumstances within the airline's control (e.g., maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc.).

Extreme Weather: Significant meteorological conditions (actual or forecasted) that, in the judgment of the carrier, delays or prevents the operation of a flight such as tornado, blizzard or hurricane.

National Aviation System (NAS): Delays and cancellations attributable to the national aviation system that refer to a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control.

Late-arriving aircraft: A previous flight with same aircraft arrived late, causing the present flight to depart late.

Security: Delays or cancellations caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas.

ANALYSIS

The normal distribution test results of the delay data of Southwest Airlines are shown in Table 1.

Table 1. The normal distribution test results of the delay data of Southwest Airlines

VARIABLES	SKEWNESS	KURTOSIS	KOLMOGOROV-SMIRNOV	
	STATISTIC	STATISTIC	STATISTIC	P
Air Carrier Delay	0,447	0,787	0,059	0,061
Weather Delay	-0,170	-0,389	0,035	0,200
NAS Delay	-0,699	1,252	0,052	0,200
Security Delay	0,712	2,119	0,079	0,002
Aircraft Arriving Late	-0,840	1,619	0,079	0,002
Total Delay	-0,370	0,944	0,048	0,200

Kim (2013) stated that for medium-sized samples ($50 < n < 300$), reject the null hypothesis at absolute z-value over 3.29, which corresponds with an alpha level 0.05, and conclude the distribution of the sample is non-normal (Kim, 2013). For this reason, it can be assumed that data of aircraft arriving late of Southwest Airlines has normal distribution even if the p-value $< 0,05$.

The normal distribution test results of the delay data of American Airlines are shown in Table 2.

Table 2. The normal distribution test results of the delay data of American Airlines

VARIABLES	SKEWNESS	KURTOSIS	KOLMOGOROV-SMIRNOV	
	STATISTIC	STATISTIC	STATISTIC	P
Air Carrier Delay	0,216	1,008	0,025	0,200
Weather Delay	0,378	0,013	0,046	0,200
NAS Delay	-0,001	0,443	0,046	0,200
Security Delay	1,226	6,282	0,130	0,000
Aircraft Arriving Late	-0,387	0,625	0,056	0,094
Total Delay	-0,162	0,647	0,040	0,200

Security delay of American Airlines has not normal distribution because of skewness and kurtosis. Therefore, security delay data of neither American Airlines nor Southwest Airlines were included in the analysis so that the analysis could be done under equal terms. The hierarchical regression results Southwest Airlines are shown in Table 3.

Table 3. Examination of the predictive role of delay reasons on total delays of Southwest Airlines by hierarchical regression analysis

		UNSTANDARDIZED COEFFICIENTS		STANDARDIZED COEFFICIENTS		
MODEL		B	STD. ERROR	BETA	T	P
1	(Constant)	1.041	0.125		8.347	0.000
	Air Carrier Delay	1.546	0.057	0.877	27.075	0.000
2	(Constant)	0.609	0.066		9.294	0.000
	Air Carrier Delay	0.744	0.043	0.422	17.259	0.000
	Aircraft Arriving Late	0.748	0.030	0.615	25.169	0.000
3	(Constant)	0.542	0.066		8.263	0.000
	Air Carrier Delay	0.792	0.043	0.449	18.271	0.000
	Aircraft Arriving Late	0.654	0.037	0.538	17.714	0.000
	Weather Delay	0.340	0.084	0.088	4.033	0.000
4	(Constant)	0.189	0.062		3.047	0.003
	Air Carrier Delay	0.706	0.036	0.401	19.689	0.000
	Aircraft Arriving Late	0.485	0.034	0.399	14.426	0.000
	Weather Delay	0.223	0.069	0.058	3.245	0.001
	NAS Delay	0.554	0.051	0.242	10.834	0.000

Model 1: $r^2 = 0.769$ $F_{(1,219)} = 733.035$ p= 0.000 Total Delay= 1.041+Air Carrier Delay*1.546

Model 2: $r^2 = 0.941$ $F_{(2,218)} = 1741.759$ p= 0.000 Total Delay= 0.609+Air Carrier Delay*0.744+Aircraft Arriving Late*0.748

Model 3: $r^2 = 0.944$ $F_{(3,217)} = 1247.896$ p= 0.000 Total Delay= 0.542+Air Carrier Delay*0.792+Aircraft Arriving Late*0.654+Weather Delay*0.340

Model 4: $r^2 = 0.964$ $F_{(4,216)} = 1467.232$ p= 0.000 Total Delay= 0.189+Air Carrier Delay*0.706+Aircraft Arriving Late*0.485+Weather Delay*0.223+NAS Delay*0.554

Dependent Variable: Total Delay

The hierarchical regression results American Airlines are shown in Table 4.

Table 4. Examination of the predictive role of delay reasons on total delays of American Airlines by hierarchical regression analysis

		UNSTANDARDIZED COEFFICIENTS		STANDARDIZED COEFFICIENTS		
MODEL		B	STD. ERROR	BETA	T	P
1	(Constant)	0.195	0.252		0.776	0.438
	Air Carrier Delay	2.108	0.109	0.795	19.419	0.00
2	(Constant)	1.119	0.177		6.332	0.00
	Air Carrier Delay	0.241	0.125	0.091	1.922	0.056
	Aircraft Arriving Late	1.242	0.069	0.845	17.881	0.00
3	(Constant)	0.876	0.144		6.074	0.00
	Air Carrier Delay	0.365	0.102	0.138	3.591	0.00
	Aircraft Arriving Late	0.961	0.062	0.655	15.59	0.00
	Weather Delay	0.705	0.065	0.276	10.868	0.00
4	(Constant)	0.100	0.095		1.045	0.297
	Air Carrier Delay	0.704	0.061	0.266	11.588	0.00
	Aircraft Arriving Late	0.482	0.042	0.329	11.426	0.00
	Weather Delay	0.417	0.040	0.163	10.476	0.00
	NAS Delay	0.585	0.028	0.399	20.939	0.00

Model 1: $r^2 = 0.631$ $F_{(1,219)} = 377.090$ $p= 0.000$ Total Delay= 0.195+Air Carrier Delay*2.108

Model 2: $r^2 = 0.850$ $F_{(2,218)} = 622.815$ $p= 0.000$ Total Delay= 1.119+Air Carrier Delay*0.241+Aircraft Arriving Late*1.242

Model 3: $r^2 = 0.902$ $F_{(3,217)} = 677.640$ $p= 0.000$ Total Delay= 0.876+Air Carrier Delay*0.365+Aircraft Arriving Late*0.961+Weather Delay*0.705

Model 4: $r^2 = 0.968$ $F_{(4,216)} = 1642.370$ $p= 0.000$ Total Delay= 0.100+Air Carrier Delay*0.704+Aircraft Arriving Late*0.482+Weather Delay*0.417+NAS Delay*0.585

Dependent Variable: Total Delay

RESULTS

Table 3 shows the results of the predictive role of delay reasons on total delays of Southwest Airlines by hierarchical regression analysis. In the first model, the effect of air carrier delay on total delays is examined. The effect of air carrier delays on total delays is statistically significant ($p< 0.05$). It is analyzed that air carrier delay explained 76.9% of the variability in total delays ($r^2= 0.769$). In the second model, aircraft arriving late variable is added. The effect of both air carrier delay and aircraft arriving late variables on total delay is statistically significant ($p< 0.05$). It is determined that the variables of air carrier delay and aircraft arriving late together explains 94.1% of the variability on the total delay ($r^2= 0.941$). It is observed that aircraft arriving late variable added to second model increased revealable rate of the variability in total delay by 17.2%. In the third model, weather delay variable is added. The effect of each of the variables of air carrier delay, aircraft arriving late and weather delay on total delay is statistically significant ($p< 0.05$). It is analyzed that the total effect of these three variables explains 94.4% of the variability in total delay ($r^2= 0.944$). It is observed that weather delay variable added to third model increased revealable rate of the variability in total delay by 3‰. In the fourth model, NAS delay variable is added. The cumulative effect of the four variables on total delay is statistically significant ($p< 0.05$). It is obviously shown that the total effect of these four variables explains 96.4% of the variability in total delay ($r^2= 0.964$). It can be said that NAS delay variable added to fourth model increased revealable rate of the variability in total delay by 2%. The established hierarchical regression model was statistically significant ($F_{(4,216)} = 1467.232$, $p< 0.05$).

Table 4 shows the results of the predictive role of delay reasons on total delays of American Airlines by hierarchical regression analysis. In the first model, the effect of air carrier delay on total delays is examined. The effect of air carrier delays on total delays is statistically significant ($p< 0.05$). It is analyzed that air carrier delay explained 63.1% of the variability in total delays ($r^2= 0.631$). In the second model, aircraft arriving late variable is added. The effect of both air carrier delay and aircraft arriving late variables on total delay is statistically significant ($p< 0.05$). It is determined that the variables of air carrier delay and aircraft arriving late together explains 85% of the variability on the total delay ($r^2= 0.850$). It is observed that aircraft arriving late variable added to second model increased revealable rate of the variability in total delay by 21.9%. In the third model, weather delay variable is added. The effect of each of the variables of air carrier delay, aircraft arriving late and weather delay on total delay is statistically significant ($p< 0.05$). It is analyzed that the total effect of these three variables explains 90.2% of the variability in total delay ($r^2= 0.902$). It is observed that weather delay variable added to third model increased revealable rate of the variability in total delay by 5.2%. In the fourth model, NAS delay variable is added. The cumulative effect of the four variables on total delay is statistically significant ($p< 0.05$). It is obviously shown that the total effect of these four variables explains 96.8% of the variability in total delay ($r^2= 0.968$). It can be said that NAS delay variable added to fourth model increased revealable rate of the variability in total delay by 6.6%. The established hierarchical regression model was statistically significant ($F_{(4,216)} = 1642.370$, $p< 0.05$).

CONCLUSION

The trend of increasing demand for air transport and the problem of congestion at airports are directly proportional. In the literature, it is tried to minimize the negative effects of this problem with price and quantity-based approaches. The aim of the research is to determine the predictive role of delay reasons on total delays in the context of the airline business model. Southwest Airlines, the low-cost carrier, is more punctual than the full-service carrier, American Airlines, when comparing the two air carriers based on total delays. While this has the potential to change with the increase in the number of airlines in the sample, lower turnaround times can be anticipated for low-cost airlines. However, this study presents a detailed comparison of the two airlines that has adopted two different airline business models by attributing the delays caused by the carrier to the airline business model. Even though Southwest Airlines has a shorter turnaround time and more punctual than American Airlines, its predictive role of air carrier delay on total delay is more than American Airlines'. It is thought that the delays may also be related to the slot levels of the airports in the flight networks of the airline companies and the systemic delays of these airports. From this perspective, airports with the same and different slot levels will be compared based on delays caused by the aviation system in further studies.

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Contribution by author: FI: Conceptualization; methodology; formal analysis; investigation; resources; writing—original draft preparation; writing—review and editing. SSA: Conceptualization; investigation; writing—review and editing; supervision.

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