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COVID-19, FINANCIAL RISK AND THE AIRLINE INDUSTRY

KOVID-19, FİNANSAL RİSK VE HAVAYOLU SEKTÖRÜ

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Abstract

The aim of this study is to investigate the effect of firm spesific factors on the bankruptcy risk of airlines. In this study, financial variables that affect financial distress in airlines and the possibility of bankruptcy were analyzed. In the framework of the study, the financial data from 35 airlines were examined. We employed the Altman (1968) Z-score, Springate (1978) S-score and Zmijewski (1984) J-score financial distress prediction models. The findings indicate that in times of crisis, when the probability of financial distress and bankruptcy increases (such as with Covid-19), leverage level, asset structure, firm size, firm profitability and liquidity ratio have a significant effect on an airline's probability of bankruptcy score.

Keywords: Financial Risk, Airline Industry, Financial Distress Prediction Models.

Öz

Bu çalışmanın amacı, firmaya özgü faktörlerin havayollarının iflas riski üzerindeki etkisini araştırılmasıdır. Bu çalışmada, havayollarında finansal sıkıntıyı veya iflas olasılığını etkileyen finansal değişkenler incelenmiştir. Çalışma kapsamında 35 havayolunun finansal verileri analiz edilmiştir. Altman (1968) Z-skor, Springate (1978) S-skor ve Zmijewski (1984) J-skor finansal sıkıntı tahmin modellerinden yararlanılmıştır. Bulgular, kriz zamanlarında diğer bir ifadeyle finansal sıkıntı ve iflas olasılığının arttığı durumlarda (Covid-19 gibi), kaldıraç seviyesi, varlık yapısı, firma büyüklüğü, firma karlılığı ve likidite oranı değişkenlerinin havayolu finansal sıkıntı veya iflas olasılığını anlamlı ölçüde etkilediğini göstermektedir.

Anahtar Kelimeler: Finansal Risk, Havayolu Sektörü, Finansal Sıkıntı Tahmin Modelleri.

GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Kovid-19 gibi kriz dönemlerinde havayollarının finansal sıkıntı veya iflas yaşama olasılığı artmaktadır. Literatürde işletmelerin iflas riskinin ortaya çıkarılması için çeşitli modeller geliştirilmiştir. İşletmelerin iflas riskini ortaya çıkarmak amacıyla yaygın bir şekilde kullanılan modellerin başında Altman (1968) Z-skoru, Springate (1978) S-skoru ve Zmijewski (1984) J-skoru gelmektedir. Bu çalışmada havayollarının iflas olasılığını etkileyen belirleyici değişkenlerin tespit edilecektir. Dolayısıyla bu çalışmanın amacı, havayollarının finansal sıkıntı veya iflas riskini etkileyen finansal faktörlerin ortaya çıkarılmasıdır.

Araştırma Soruları

Havayollarının finansal sıkıntı veya iflas riskini etkileyen finansal faktörler nelerdir? Kriz dönemlerinde finansal sıkıntı ve iflas olasılığı artmaktadır. Dolayısıyla finansal belirleyicileriden hareketle kriz (Kovid-19 gibi) öncesi dönemlerde hangi havayolunun krizden daha fazla etkileneceğini öngörmek mümkün müdür?

Literatür Araştırması

Literatürde işletmelerin karşı karşıya kaldıkları sistematik risk ve sistematik olmayan riskler ile ilgili çeşitli çalışmalara rastlanmaktadır. Bunun yanında havayolu endüstrisinde işletmelerin maruz kalabileceği risklerin (özellikle petrol fiyatlarındaki artışa bağlı riskler) ele alındığı çalışmalar yapılmıştır. Bu riskleri ele alan çalışmalarda hedging sözleşmelerine bağlı ortaya çıkan riskler ve bunların etkileri incelenmiştir. Havayolu endüstrisinde iflas riski veya sıkıntı tahmin modellerinin kullanılarak, riski belirleyen faktörlerin incelendiği çalışmaların sınırlı sayıda kaldığı görülmektedir. Buna ek olarak, Kovid-19 bağlamında bu konunun incelendiği hiçbir çalışmaya rastlanmamıştır.

Yöntem

Bu çalışmada panel veri analizi yöntemi kullanılarak havayollarının finansal sıkıntı veya iflas riskini etkileyen finansal faktörler araştırılmıştır. Panel veriler, zaman serileri ve yatay kesit verilerinin birleştirilmesiyle oluşturulan verilere boylamsal veriler veya panel veriler denmektedir. Son zamanlarda literatürde yaygın bir şekilde kullanılmaya başlanan panel veri analizi, ekonomik araştırmalarda, finansal ilişkilerin ortaya çıkarılmasında ve daha birçok sosyal bilim analında kullanılmaktadır. Panel veri kullanımının yatay kesit veya zaman serilerine göre birçok avantajı söz konusudur.

Sonuç ve Değerlendirme

Çalışmanın bulguları, havayolu şirketlerinin finansal sıkıntı veya iflas olasılığını hangi finansal oranın veya değişkenin etkilediği ile ilgili detaylı bilgiler içermektedir. Buna ek olarak hangi finansal göstergenin finansal sıkıntı veya iflas olasılığını pozitif veya negatif etkilediğini de göstermektedir. Havayollarının finansal tablolarının detaylı bir şekilde incelenmesi ile hangi havayolunun mali sıkıntı yaşama ihtimalinin daha yüksek olduğunun bu çalışma ile görülebileceği düşünülmekdir. Bu kapsamda çalışmanın sonuçları şu şekilde özetlenebilir. Karlılık oranı ile iflas olasılığı skoru arasında pozitif bir ilişki vardır, bu da havayollarının karlılık oranı arttıkça finansal zorluk olasılığının azaldığını göstermektedir. Nakit akış oranı ile iflas olasılığı skoru arasında pozitif bir ilişki vardır. Model 1 ve Model 2 için elde edilen bulgular, firma büyüklüğü ile iflas olasılığı puanı arasında pozitif bir ilişki olduğunu göstermektedir. Cari oran ile iflas olasılığı skoru arasında pozitif bir ilişki vardır. Bu, mevcut varlıkların seviyesindeki bir artışın veya havayollarındaki tutarlı nakit akışlarının, finansal başarısızlık veya iflas riski olasılığında bir azalmaya yol açacağına işaret etmektedir. Kaldıraç oranı ile iflas olasılığı puanı arasında negatif bir ilişki vardır. Havayollarının borç seviyelerindeki bir düşüşün aslında finansal başarısızlık veya iflas riski olasılığını artırdığını göstermektedir. Model 3'ün bulguları, kısa vadeli borç oranı ile iflas olasılığı arasında negatif bir ilişki olduğuna işaret etmektedir. Ancak bu bulgu teorik beklentilere aykırıdır. Bunun yanı sıra maddi duran varlıklar ile iflas olasılığı arasında anlamlı ve pozitif bir ilişkisi olduğu görülmüştür. Bu durum, filodaki uçak sayısı ve havayollarının firma büyüklüğü ile ilgili olabilir. Söz konusu bulgu teorik beklentilerle uyumludur.

1. INTRODUCTION

Forecasting, measuring, alleviating and evaluating the bankruptcy risk of a firm has been a long-standing focus for investors in advance of investing their capital. Nevertheless, value maximization may only take place if providers of capital selectively choose a sustainable and profitable business from which they can obtain the greatest portion of business income (Agustia, Muhammad and Permatasari, 2020). The investments that investors make or plan to realize gain more importance during times of crisis. Making the right investment decisions in such situations maximizes investors' wealth. However, making erroneous decisions may cause investors to experience significant losses. It is especially vital that investors make the right decisions in the airline industry, which operates in an environment where there are many systematic and non-systematic risks.

In the history of aviation, there have been many crises that have caused airlines to suffer financial distress and/or bankruptcy. These crises led to an increase in costs and/or a decrease in income in the industry. For example; the 1970s oil crisis had an adverse effect on the air transport sector. The Gulf War, in the early 1990s, caused an increase in costs due to the increase in oil prices. After the September 11 terrorist attack, many airlines that experienced cost pressure and demand shrinking went bankrupt. Therefore, global crises, terrorist attacks and epidemic diseases may cause airlines to have financial difficulties and/or bankruptcy (Gittell, et al.,2006). The recent global pandemic has been had a similar effect on the airlines industry. Due to Covid-19, the demand for airlines halted almost completely. Many global airlines have completely suspended their scheduled flights due to low demand, travel bans, and airspace restrictions. Airlines, whose cash flows have deteriorated, are more likely to experience financial distress or even bankruptcy (Mahtani and Garg, 2018). However, it is significant to know which airlines will be more affected by the Covid-19 pandemic. Therefore, it is important to measure the financial risk of airlines and examine the determinants of that exposure. Through analysis of the determinants of financial risk, the airlines which will be more successful or less successful in the Covid-19 crisis can be foreseen.

Within the last few decades, the airline industry has become exposed to an oil crisis, the Gulf War, the September 11 terrorist attack, the SARS outbreak, and the 2008 global financial crisis. Several studies in the literature have assessed the impact of these crises on the air transport industry (Hätty and Hollmeier, 2003; Drakos, 2004; Guzhva and Pagiavlas, 2004; Walker, 2005; Bock et al., 2020). The crises experienced can lead to increased costs for airlines (Charalambakis, Evangelos C; Espenlaub, Susanne K; Garrett, 2008), deteriorated cash flow, and reduced passenger demand. Crises also cause airlines to experience the risk of financial distress and/or bankruptcy. Although airlines have developed various methods to reduce the impact of a crisis (Merkert and Morrell, 2012) and gain a competitive advantage (Swidan and Merkert, 2019; Swidan, Merkert and Kwon, 2019) these are often insufficient

(Swidan, Merkert and Kwon, 2019) and the airlines only continue their operations through public support, such as via state subsidies.

The air transport industry is one of the sectors that are most affected by the Covid-19 pandemic (Nižetić, 2020). Many airlines have reduced or halted their operations. This may cause a deterioration of cash flow and lead to financial difficulties. Forecasts indicate that the reduction of international air passenger traffic will range from 44% to 80% in 2020 compared to 2019. According to the scenarios regarding Covid-19's impact on international passenger traffic, the expected loss of gross operating revenues of airlines is 153 to 273 billion dollars for 2020 (ICAO, 2020). It is inevitable that many airlines will experience financial difficulties or bankruptcy due to Covid-19. This situation raises the questions as to which financial ratios can be important about airlines to be more or less affected by Covid-19. In order to find the answer to this question, it is important to analyze the factors that determine financial risk in airlines. In this context, we firstly determined the risk of the probability of bankruptcy of airlines by using financial distress prediction models. Secondly, we analyzed the impact of the financial ratios on the probability of bankruptcy of airlines. By finding out the financial factors affecting the probability of bankruptcy, we have provided valuable information about which airlines will be more affected by Covid-19. In the study, the approach we have adopted allows the financial condition of the company to be monitored using financial ratios.

The research motives of this study, in which the financial determinants of bankruptcy risk were analyzed, are as follows.

• To identify the major financial factors which influence financial failure or the bankruptcy risk of airlines.

• To reveal empirically which financial variables/ratios increase or decrease the likelihood of bankruptcy for airlines that are at risk of financial failure due to Covid-19.

• To predict which airlines, have temporarily halted operations, reduced flight frequency, and/or have relative flexibility in flight operations, will be most affected by the Covid-19 pandemic by looking at their financial statements

• To provide stakeholders with information about the “real financial situation” of airlines, by monitoring the changes in financial variables, using past financial statements.

The rest of the study is structured as follows. In Section 2, the literature review used in the study is discussed. In Section 3, the methodological framework, financial distress prediction models, and research model of this study are explained in detail. In Section 4, the data sources and empirical findings of the research are evaluated. Additionally, in this section, the empirical analysis results of the financial indicators on the risk of airline bankruptcy are presented. In Section 5, the results of this study are discussed.

2. LITERATURE REVIEW

The airline industry is sensitive to systematic risks that are triggered by many uncontrollable external factors, such as war, the threat of terrorism, outbreaks of diseases, global economic regression, and high fuel prices. Drakos (2004) was among the first researchers to examine the effect of the September 11 terrorist attack on the financial risk of airlines by utilizing the Market Model and investigating the effects of terror attacks on airline stocks. The results demonstrate that not only the systematic risk but also idiosyncratic risk increase. Loudon (2004) analyzed the financial risks of Australian and New Zealand airlines. The interest rate, fuel price and currency risk that airlines were exposed to was examined for the years 1995-2003. Results point out that the terrorist attacks and the collapse of major competitors meant that the financial risks were largely unchanged. Lee & Jang (2007) investigated the effect of firm-specific variables on systematic risk (beta) in airlines. Data of 16 airlines for the 1997-2002 period were analyzed. The findings indicate that growth opportunity, profitability and safety negatively affect systematic risk, yet leverage and firm size affect systematic risk positively. Chee-Wooi et al., (2010) analyzed the East Asian airline industry systematic risks exposure in the period 1993-2009. Their research shows that firm size and operating efficiencies positively affect systematic risk. Kiraci (2018), on the other hand, examined the determinants of financial risk in airlines that apply to the low-cost business model. He analyzed the financial data of 13 airlines for the period 2004-2017. The findings revealed that debt level, asset structure, size, profitability, and liquidity significantly affect financial risk.

During volatile periods, such as after terrorist attack, epidemic, war, and economic regression, hedging strategies can allow airlines to achieve competitive advantages by price freezing for future input requirements (Merkert and Swidan, 2019). Hedging strategies can play a vital role in financial risk management in times of crisis. However, when prices decrease sharply, hedging strategies become disadvantageous for airlines. Various studies have been conducted on hedging strategies and risk exposure reduction in the air transport literature. Berghöfer & Lucey (2014) focused on financial and operational hedging strategies for the Asian and European airline market. 64 airlines were analyzed for an 11-year period. According to the findings, the hypothesis that financial hedging decreases risk exposure was rejected. Shaeri et al., (2016) examined oil price risk exposure over the period 1983-2015 for industries including the airline industry. Findings indicate that airlines have the largest negative oil price risk exposure. Turner & Lim (2015) analyzed hedge jet fuel price risk with futures for airlines hedging with futures. Daily data from the previous 20 years were used. Findings point out futures that would create the most efficient hedge by using heating oil futures agreements with a 3-month maturity. Lim & Hong (Lim and Hong, 2014) investigated the role of fuel hedging in diminishing airlines' operating costs. US airlines data was used for the period 2000-2012. Results show that fuel hedging airlines had approximately 9–12% lower operating costs, but this finding was not statistically significant. Swidan & Merkert (2019) evaluated the cost impact of operational hedging and the relationship between operational hedging and financial hedging. 80 global airlines data were analyzed for fiscal consecutive years from 2010/2011 to 2013/2014. Findings demonstrate that operational hedging based on aircraft engine commonality significantly diminishes operating cost. Merkert & Swidan (2019) investigated the effect of hedging on airline financial performance in the context of financial risk. The study was based on data from 100 international airlines for a six-year period. Results show that fuel price hedging was significantly effective in mitigating financial risks. Swidan et al., (2019) examined airlines' benefits and costs of hedging activities using the Value at Risk (VAR) model. Findings indicate that jet fuel hedging can significantly reduce market risk exposure.

Due to the Covid-19 pandemic, the risk of financial distress and bankruptcy of airlines has increased. Several studies have been conducted in the literature examining the impact of Covid-19 on the airline industry. For instance; Pereira and Mello (2021) analyzed the efficiency of the Brazilian airlines during Covid-19. Budd et all., (2020) examined the responses of major airlines to the Covid-19 crisis. Maneenop and Kotcharin (2020) examined the short-term impact of the Covid-19 pandemic on the global airline stock performance. Albers and Rundshagen (2020) investigated the strategic responses of European airlines to the 2019 novel coronavirus (Covid-19) outbreak. Abate et al., (2020) examined the effect of the travel restriction on the air transport sector following the outbreak of the Covid-19 pandemic. However, there are a limited number of studies in the literature examining the relationship between airway financial risk and Covid-19.

It is a widely used method to analyze the financial condition of the company using financial statements. Through financial distress prediction models, it can be determined whether firms have a financial risk by using the financial ratios. In the literature, the first model was developed by Beaver (1966) who proposed the total debt ratio of cash flow to predict bankruptcies. Following this model Altman et al., (1977), Altman (1968), Fulmer et al., (1984), Ohlson (1980), Springate (1978), and Zmijewski (1984) created financial distress prediction models. These models make bankruptcy predictions using financial ratios. By using these models, the financial distress and bankruptcy possibilities of the companies can be determined. In this study, the financial determinants of bankruptcy will be analyzed for airlines using the Altman (1968), Springate (1978), and Zmijewski (1984) financial distress prediction models. In this study, financial determinants of bankruptcy risk will be analyzed for airlines by using financial distress prediction models. There are many studies in the literature analyzing airline financial risk, however, in this study; we used financial distress prediction models which have rarely been studied. Furthermore, we analyzed the financial ratios affecting airlines' probability of bankruptcy. Therefore, we focused on which financial ratios increase the probability of bankruptcy score for airlines whose financial distress risk increases during times of crisis.

3. METHODOLOGICAL FRAMEWORK

3.1. Panel Data Analysis

The data formed by combining time series and horizontal section data is called longitudinal data or polled data. The time and horizontal cross-section dimensions of such data may differ. Longitudinal data, in which the horizontal section units remain unchanged, is called panel data (Güriş, 2015). In economic research, panel data usage has many advantages over a horizontal section or time series. In panel data analysis, more observations are obtained compared to the cross-section and time series. This increases the degree of freedom and reduces the collinearity between the independent variables. Using panel data, increases the effectiveness of econometric forecasts in research (Hsiao, 2014).

Panel data is created by including N units and T observations of each unit in the same data set (Tatoğlu, 2013). In panel data analysis, i subscripts are used to indicating the units and t subscripts to indicate the time period. The linear panel data model created with the panel data, where the dependent variable Y is indicated by independent variables X, is as follows.

Panel data equation, i cross-section units (i=1,…,N), t change over time (t=1,…,N) and the dependent variable Y, by displaying the independent variables with X. This can be defined as Y_it=α_it+β_it X_it+Ɛ_it. Here Ɛ_it exhibits the error terms.

3.2. Financial Distress Prediction Models

3.2.1. Altman Z-Score Model

The most widely used financial distress prediction model is the Z-score method created by Altman in 1968. Altman (1968) examined companies that filed for bankruptcy in the USA between 1946 and 1965. Altman's financial distress prediction model has quite successful results in predicting failure. In later periods, the model was revised and applied to different sectors. Altman created the Z" Model in 1993. This model typically has significantly successful results for retail and service firms in comparison to manufacturing firms under-predict bankruptcy. In the Altman Z-score, financial variables are proportioned. By multiplying these ratios by some coefficients, a positive linear function is obtained. For private and non-manufacturing firms, the developed Z" Score models of bankruptcy prediction model is as follows (Hayes, Hodge and Hughes, 2010).

$\boldsymbol{\alpha}$ = Working Capital / Total Assets

$\boldsymbol{\beta}$ = Retained Earnings / Total Assets

$\boldsymbol{\gamma}$ = EBIT / Total Assets

$\boldsymbol{\delta}$ = Market Value / Total Liabilities

Z" - Score = 6.5 $\boldsymbol{\alpha}$ + 3.26 $\boldsymbol{\beta}$ + 6.72 $\boldsymbol{\gamma}$ + 1.05 $\boldsymbol{\delta}$

After the Z-Score value is calculated through the equation above, the financial failure of the firm can be estimated at certain intervals. If Z <1.1, the financial failure risk of the company is quite high. If the financial failure score is in the range of 1.1 <Z <2.6, there is no risk of financial failure for the company but the company is not considered financially successful either. Altman Z " score, if Z> 2.6, the company does not have any financial distress or financial failure risk, the firm is financially successful.

3.2.2. Springate S-Score Model

The Springate S-score model was created by Gorgon Springate in 1978. This model makes bankruptcy prediction in the framework of multiple discriminant analysis. The Springate S-score is acquired by proportioning financial parameters to each other. The financial ratios obtained are multiplied by certain coefficients to obtain the final S-score. Financial ratios using S-score models of bankruptcy prediction and their equation are as follows.

$\boldsymbol{\alpha}$ = Working Capital / Total Assets

$\boldsymbol{\beta}$ = Retained Earnings / Total Assets

$\boldsymbol{\varphi}$ = EBIT / Short Term Debt

$\boldsymbol{\theta}$ = Sales / Total Assets

$$S\text{ - Score} = 1.03\,\boldsymbol{\alpha} + 3.07\,\boldsymbol{\beta} + 0.66\,\boldsymbol{\varphi} + 0.4\,\boldsymbol{\theta}$$

For The Springate S score, if the result score is lower than 0.862 in the calculation made using the equation above, there is a possibility of financial failure of the firm.

3.2.3. Zmijewski (1984) J-Score Model

Zmijewski (1984) J-score model of bankruptcy prediction uses financial ratio analysis that measures level of performance of liabilities and liquidity of a firm. In this analysis, Zmijewski used probit analysis as implemented to 40 firms in a position of bankruptcy and 800 firms that were still operating at the time, and then established a model by utilizing financial ratios that measured firm performance, liquidity, and leverage (Husein and Pambekti, 2015). The ratios were not selected according to theoretical basis, yet rather on the framework of their performance in previous research (Grice and Dugan, 2003). Zmijewski’s bankruptcy prediction probit model is shown in the equation below.

Φ = Net Profit / Total Assets

ξ = Total Debt / Total Assets

η = Current Asset / Short Term Liabilities

$$J\text{ - Score} = -\ 4.3 - 4.5\ \Phi + 5{,}7\ \xi + 0{,}04\ \eta$$

In the calculation using the above equation for Zmijewski J-score, if the score is below 0.5, there is a risk of financial failure for the firm.

3.3. Research Model

Financial distress prediction models are employed to measure the risk of financial distress or even bankruptcy. Using these models, the probability of bankruptcy score of airlines can be established. Then, empirical models of the study, in which the probability of bankruptcy score is used as dependent variable, are determined. The empirical models used in this study can be demonstrated through the following equations:

$$\mathrm{PB} = \mathrm{f}(\mathrm{STD}, \mathrm{FAR}, \mathrm{PR}, \mathrm{CFR}, \mathrm{FS}, \mathrm{CR}, \mathrm{LR}) \quad (3.1)$$

Equation (3.1) could be demonstrated in a panel form following procedure.

$$\mathrm{PB_{it}} = \mathrm{X_{it}} + \varepsilon_{\mathrm{it}} \quad (3.2)$$

Accordingly, to specify the aforementioned error structure for the disturbance term, we have:

$$\varepsilon_{\mathrm{it}} = \alpha_{\mathrm{it}} + \gamma_{\mathrm{t}} + \eta_{\mathrm{it}} \quad (3.3)$$

Where

$\alpha_{\mathrm{it}} \Rightarrow$ Expresses the unobservable specific cross-section effects cross

$\gamma_{\mathrm{t}} \Rightarrow$ Express unobservable specific time effects

$\eta_{\mathrm{it}} \Rightarrow$ Express the mutual cross section time series effect

From equation (3.2), $\mathrm{X_{it}}$ contains the independent variables to be employed in the model:

Using the financial distress prediction models, 3 new models are created as follows:

Model 1:

$$\mathrm{ZS_{it}} = \beta_0 + \beta_1\mathrm{STD_{it}} + \beta_2\mathrm{TA_{it}} + \beta_3\mathrm{PR_{it}} + \beta_4\mathrm{CFR_{it}} + \beta_5\mathrm{FS_{it}} + \beta_6\mathrm{CR_{it}} + \beta_7\mathrm{LR_{it}} + \varepsilon_{\mathrm{it}} \quad (3.4)$$

Model 2:

$$\mathrm{SS_{it}} = \beta_0 + \beta_1\mathrm{STD_{it}} + \beta_2\mathrm{TA_{it}} + \beta_3\mathrm{PR_{it}} + \beta_4\mathrm{CFR_{it}} + \beta_5\mathrm{FS_{it}} + \beta_6\mathrm{CR_{it}} + \beta_7\mathrm{LR_{it}} + \varepsilon_{\mathrm{it}} \quad (3.5)$$

Model 3:

$$\mathrm{JS_{it}} = \beta_0 + \beta_1\mathrm{STD_{it}} + \beta_2\mathrm{TA_{it}} + \beta_3\mathrm{PR_{it}} + \beta_4\mathrm{CFR_{it}} + \beta_5\mathrm{FS_{it}} + \beta_6\mathrm{CR_{it}} + \beta_7\mathrm{LR_{it}} + \varepsilon_{\mathrm{it}} \quad (3.6)$$

PB = Probability of bankruptcy (Altman Z Score; Springate S-score and Zmijewski J-score).

ZS = Altman Z - Score financial distress prediction model

SS = Springate S - Score financial distress prediction model

JS = Zmijewski J - Score financial distress prediction model

STD = Short term debt ratio

TA = Tangible assets

PR = Profitability ratio

CFR = Cash flow ratio

FS = Firm size

CR = Current ratio

LR = Leverage rate

β_0 = Constant term of the models.

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$ are the coefficients of the models.

ε = The error term of the model, this variable describes another variable that influencing the probability of bankruptcy score not captured by this model.

Where $i = 1, \dots, 35$ and $t = 2004, 2005, \dots, 2018$

For the 3 models created, 3 different dependent variables were used. However, the independent variable in the model remained the same.

In Model 1, we used the Z-score, a financial distress prediction model. We included the S-score in Model 2 as an independent variable. The higher scores in a financial distress prediction model indicate that firms are less likely to suffer financial distress or bankruptcy. However, low scores indicate that firms' financial risk has increased. As a result of the analysis, the positive effect of the coefficient on the scores indicates that it has a negative effect on financial risk. However, if the effect of the variable coefficient on the scores is negative, it indicates an increase in the financial risk of the firm. In Model 3, we used Zmijewski's J-score financial distress prediction model. The independent variables used in the study were determined as short-term debt ratio, tangible assets, profitability ratio, cash flow ratio, firm size, current ratio, and leverage rate. Following this section, the hypotheses of the study, and the possible impact of its variables on the probability of bankruptcy score, are given.

3.4. Hypothesis Development

3.4.1. Short Term Debt

According to He & Xiong (2012) debt market illiquidity swells out a firms' default probability through the rollover risk or maturity risk channel. Rollover risk amounts to the conditions when firms' funding costs increase unfavorably and they suffer heavy losses from using new debts to replace maturing liabilities (Wang and Chiu, 2019, p. 2). Especially in companies using short term debt, the maturity risk arises due to the short period of debt. In addition, firms with more short-term debt or with shorter debt maturity came up against greater default risk during the credit crisis (He and Xiong, 2012).

Theoretically, in cases where the firm has a rollover risk, shareholders want to take more risk to keep their firms alive. However, debt holders want to preserve principal payments and prevent the firm from taking risks. This conflict between shareholders and debt holder causes the company to experience financial distress in a shorter time than it should (Della Seta, Morellec and Zucchi, 2020). Capital structure theories also offer remarkable suggestions on the relationship between short-term debt ratio and firm risk. According to both the Finance Hierarchy and the Trade-off theory, the increase in firm debt increases the risk of the firm. Studies on short term debt, financing risk, and default risk indicate that short-term debt increases firm default and rollover risk (Javadi and Mollagholamali, 2018; Cheng et al., 2019; Della Seta, Morellec and Zucchi, 2020).

H1. There is a negative relationship between the short-term debt ratio and the bankruptcy prediction score.

Measurement method = short-term debt / total assets

3.4.2. Tangible Assets

There is a close relationship between the firm's tangible assets and leverage (and debt maturity). A firms' tangible assets (or physical) ratio effects reducing debt costs but also increasing debt ratio (Goto and Suzuki, 2015; Saona, Vallelado and San Martín, 2019). The fact that tangible assets can create value even after bankruptcy enables firms to borrow with a lower interest rate. These firms continue their operations with a higher debt ratio. The high tangible assets ratio also facilitates debt from more channels and reduces the pressure on the borrowing company. At the same time, the firm’s tangible assets ratio is high and the debt is restructured during renegotiated crisis periods. In this case, companies with high tangible assets may be less likely to experience financial distress. According to the Asymmetric Information theory, insider learners for unlisted firms, where financial reporting requirements are low, have more specific information about asset quality. Investors find it difficult to evaluate the intangible and tangible assets of these companies (Nishihara and Shibata, 2018). In companies where the intangible assets ratio is high or the information about tangible assets is blurred, asymmetric information is greater. This can increase the probability of financial distress in the firm and bankruptcy. In our hypothesis, we predict that the ratio of tangible assets of companies will reduce the risk of financial distress and bankruptcy.

H2. There is a negative relationship between tangible assets and the bankruptcy prediction score.

Measurement method = Property, plant and equipment (PPE) / total assets

3.4.3. Profitability Ratio

The profitability ratio measures the economic viability of a company. In the long run, the company must be profitable to maintain both liquidity and solvency. (Tobback et al., 2017). In addition, there is a close relationship between the firm’s change in leverage and profitability (Ellul and Pagano, 2019). As a result, exogenous shocks to profitability can cause firms to find new external sources. If the firm is confronting debt sustainability risk, financial distress and/or bankruptcy risk appears. According to the capital structure theories, companies with high profitability can borrow at a lower cost (low interest rate). Firms with a high profitability ratio can also maintain financial solvency. Financial distress or even bankruptcy costs of such firms are also lower (Kiraci, 2019). Hence, a high and stable profitability ratio reduces financial default risk.

H3. There is a positive relationship between firm profitability and the bankruptcy prediction score.

Measurement method = net profit / total assets

3.4.4. Cash Flow

Distressed companies are more probable to obtain external financing because the excess of cash generated from operating activities is inadequate. Increasing cash outflows of firms related to operating, investing, and financing activities increases the probability of financial distress and/or bankruptcy (Shamsudin and Kamaluddin, 2015). Firms, where cash flow becomes irregular and that have difficulties in managing cash flow, experience financial distress. Firms with problems in the payment of short-term liabilities also have increased financial risk. In addition, the increase in debt costs is assumed to be effective in the investment-cash flow sensitivity of firms (Alanis and Quijano, 2019). Therefore, there is a close relationship between insufficient cash flow and the likelihood of financial distress and/or bankruptcy.

H4. There is a positive relationship between cash flow and the bankruptcy prediction score.

Measurement method = (net profit + depreciation) / equity

3.4.5. Firm Size

Firm size refers to a company's production or service capacity, quantity, and diversity. Firm size also contains valuable information about the robustness of the financial structure (Ntoiti, 2015).

Studies in the literature provide vague evidence of the relationship between firm size and the possibility of bankruptcy. For example, larger firms with greater credibility and long-term contracts in financial markets can postpone the launching of formal bankruptcy filing well beyond the point for smaller firms. On the other hand, larger firms are more sensitive to crisis or recession risk, which is linked to a firm’s financial distress and/or bankruptcy risk (Lin and Dong, 2018). However, companies have a stable and diversified cash flow that is why these firms are less likely to go bankrupt. We hypothesize is that there is a negative relationship between firm size and the possibility of financial failure.

H5. There is a positive relationship between firm size and the bankruptcy prediction score.

Measurement method = log (total assets)

3.4.6. Current Ratio

Liquidity is one of the most significant financial distress risk measurement indicators (Tykvová and Borell, 2012). Liquidity is about the turnover ratio of assets and the liquidation of assets. Liquidity is cash and securities divided by the firms' total assets (Agustia, Muhammad and Permatasari, 2020). Firms with a high liquidity ratio use their current assets instead of borrowing to fulfill their short-term liabilities. This higher financial liquidity results in a lower probability of default (Pham Vo Ninh, Do Thanh and Vo Hong, 2018). In addition, the liquidity ratio is a useful measure of whether a company can easily continue as an operating business. Firms facing financial difficulties are expected to have lower liquidity ratios than healthy ones, which have a higher margin of safety to fulfill the current liabilities (Mselmi, Lahiani and Hamza, 2017). Therefore, we expect a negative relationship between current ratio and financial risk level.

H6. There is a positive relationship between the current ratio and the bankruptcy prediction score.

Measurement method = current assets / short term liabilities

3.4.7. Leverage Ratio

The airline industry is one of the sectors with high capital density and high fixed costs. Capital intensity means a firm's greater capital intensity and operating leverage tends to increase the probability of default. The basis of this statement is the fact that a firm with a higher level of tangible assets normally experiences greater fixed costs that remain unchanged according to the firm's sales level. This implies that when demand fluctuates, the profitability of a capital intensive firm fluctuates more than a less capital intensive firm (Lee, Koh and Kang, 2011). The leverage ratio has been proposed as one of the key factors that justify a firm's financial distress, and the principle whereby the leverage ratio increases the degree of financial distress is a common assumption. The leverage ratio tends to increase a company's risk since financial markets consider highly leveraged firms to be risky as a result of implicit or explicit costs connected to their probability of financial distress. (Lee, Koh and Kang, 2011). Furthermore, firms with high operating leverage are more susceptible to economic crises and shocks due to fixed operating costs, and consequently have a higher probability of financial distress (Donangelo et al., 2019). Therefore, we expect the leverage ratio to be negatively related to the probability of bankruptcy score as the degree of leverage significantly exposes a firm to a greater risk of bankruptcy or the probability of bankruptcy score.

H6. There is a negative relationship between leverage ratio and the bankruptcy prediction score.

Measurement method = total debt / total assets

4. DATA SOURCES AND EMPIRICAL FINDINGS

In this study, the quarterly financial data of 35 airline companies for the period of 2004-2018 were examined. In the study, we included airlines whose financial data were fully available between 2004 and 2018. These airlines are the largest in the world in terms of both numbers of passengers and RPK (Revenue Passenger Kilometers). The secondary data was used in the examination of this work. The Altman Z''-score, Springate S-score, and Zmijewski J-score financial distress prediction models were employed as dependent variables in the study. The reason we employed these models in the study is that they are widely used in the literature. In addition, the financial indicators used in calculating these models are appropriate for the airline industry. The data were obtained from the Thomson Reuter Eikon datastream database. Short term debt ratio (STD), tangible assets (TA), profitability ratio (PR), cash flow ratio (CFR), firm size (FS), current ratio (CR), and leverage ratio (LR) are the explanatory variables data used in this study. Table 1 demonstrates the summary of the descriptive statistics of the dependent and independent variables.

Table 1. Descriptive Statistics

	S-score	**Z-score**	**J-score**	**STD**	**TA**	**PR**	**CFR**	**FS**	**CR**	**LR**
Mean	1.310	-0.034	-1.744	0.100	0.615	0.247	0.138	6.709	0.824	0.759
Maximum	38.62	3.661	5.849	0.567	0.895	1.772	7.523	7.778	4.051	1.693
Minimum	-5.238	-8.866	-3.988	0.001	0.077	-0.135	-4.730	4.988	0.125	0.388
Std. Dev.	2.466	1.618	0.993	0.083	0.141	0.277	0.483	0.616	0.434	0.156
Skewness	7.437	-0.988	1.213	1.583	-0.734	3.086	3.148	-0.532	2.153	1.607
Kurtosis	107.2	5.878	9.365	6.015	3.954	14.439	151.328	2.577	13.062	9.156
Jarque-Bera	926210	1019	3876	1597	256	14114	1841317	110	10007	4029
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2005	2005	2005	2005	2005	2005	2005	2005	2005	2005

The Airlines' Z-score bankruptcy prediction score has a mean of 1.31 with a standard deviation of 2.46. If the bankruptcy prediction score is between 1.1 and 2.6, there is no financial failure risk for the company. The S-score is between 3.66 and -8.86 and has a mean of -0.034 with a standard deviation of 1.6. If the S-score is less than 0.862, the firms are deemed to be at risk of financial distress. The J-score is between 5.84 and -1.744 and has a mean of -1.744 with a standard deviation of 0.993. The short term debt ratio of the analyzed airlines constitutes 10% of the mean total asset. The average fixed asset ratio of airlines is approximately 61% and the net profit to total assets ratio is approximately 24%. The ability of the airlines to meet their short-term obligations is 82% on average.

Table 2. Correlation Analysis

	STD	TA	PR	CFR	FS	CR	LR
STD	1						
TA	0.2385	1					
PR	-0.2775	-0.4679	1				
CFR	-0.1273	-0.0304	0.1194	1			
FS	0.0261	0.1606	-0.2985	0.0018	1		
CR	-0.5398	-0.3450	0.2478	0.0442	-0.1000	1	
LR	0.3825	0.0382	-0.0599	-0.0565	0.0427	-0.3831	1

Table 2 represents the correlation analysis between the variables. The correlation calculates between the firm's level of debt (profitability ratio and leverage rate) and profitability which indicates a low level of and negative correlation (-0.27 and -0.05) between the variables. Nevertheless, a positive correlation exists between tangible assets and a firm's debt ratio (short term debt and leverage ratio).

Table 3. Panel Unit Root Test

Variable	IPS W-stat		Fisher - ADF		Fisher - PP	
	Stat	p-value	Stat	p-value	Stat	p-value
Z-score	-3.90219	0.0000	124.063	0.0001	161.249	0.0000
S-score	-4.00658	0.0000	116.49	0.0004	117.239	0.0003
J-score	-4.06067	0.0000	112.166	0.0010	112.505	0.0010
STD	-4.38789	0.0000	124.707	0.0001	125.257	0.0001
TA	-1.6833	0.0462	81.1365	0.1708	82.0802	0.1531
ΔTA	-41.0948	0.0000	1247.27	0.0000	1264.88	0.0000
PR	-3.98777	0.0000	125.11	0.0001	144.181	0.0000
CFR	-5.71687	0.0000	147.152	0.0000	195.707	0.0000
FS	-1.53723	0.0621	85.408	0.1016	139.5	0.0000
CR	-1.91669	0.0276	85.6408	0.0985	106.184	0.0034
LR	-0.97634	0.1644	80.7403	0.1786	124.042	0.0001
ΔLR	-40.6903	0.0000	1224.73	0.0000	1265.15	0.0000

In this study, we employed the Im, Pasaran, and Shin (IPS) and Fisher-type tests using ADF and PP panel unit root tests to study the peculiarities of time series for the variables. Olanrewaju et al. (2019, p. 676) the important strength of the IPS test is that it enables heterogeneity on the co-efficient of the variables meanwhile suggesting a test procedure based upon the average individual unit root tests. The presumption of heterogeneity on the coefficient of the variables makes the utilization of IPS very appropriate for panel data analysis. Furthermore, the familiarity of differences in a socioeconomic and political organization in most countries enables the IPS unit root test procedure to be applicable. The results of the panel unit root test in Table 3 indicate that the Z-score, S-score, J-score, short term debt ratio, profitability ratio, cash flow ratio, firm size, and current ratio variables are stationary at levels. However, when we observe the first differences of the tangible assets and leverage ratio variables, its becomes stationary.

Table 4. Model Determination Results

	F test		LM Test		Hausman		Appropriate model
	Stat.	**p-value**	**Stat.**	**p-value**	**Stat.**	**p-value**	
Model 1	22.922	0.0000	2786.191	0.0000	26.8668	0.0004	Fixed Effects
Model 2	82.051	0.0000	12584.96	0.0000	10.0213	0.1874	Random Effects
Model 3	24.042	0.0000	3767.754	0.0000	19.3257	0.0072	Fixed Effects

After determining the integrated degrees of the variables, we considered which panel data model was appropriate We decided to apply a fixed effects analysis and a pooled regression by assessing the F Statistics test. When employing the LM Statistics test, we made a decision between a random effect analysis and a pooled model regression. Finally, we applied the Hausman test statistic value to select between random effects and fixed effects. Appropriate model determination test results demonstrate that the fixed effects for Model 1 and Model 3 and the Random Effects model for Model 2 were appropriate.

Table 5. Heteroscedasticity Test Results

Modified Wald test for heteroskedasticity				
Model - 1		Stat.	3.8e+05	
		p-value	0.0000	
Model - 3		Stat.	24403.2	
		p-value	0.0000	
Levene, Brown and Forsythe test				
	Test	W0	W50	W10
Model - 2	Stat.	21.8456	9.4883	10.9941
	p-value	0.0000	0.0000	0.0000

In the fixed effects models (Model 1 and Model 3) we used the Modified Wald test to analyze heteroscedasticity. In the random effects model (Model 2) Levene, Brown, and Forsythe test statics were used for heteroscedasticity. According to the statistic results, the H_0 null hypothesis was rejected for all models.

Table 6. Autocorrelation Test Results

Models	Durbin Watson	Baltagi–Wu
	Stat.	Stat.
Model - 1	0.1854	0.3714
Model - 2	0.3879	0.4042
Model - 3	0.3545	0.3936

Table 6 demonstrates the autocorrelation statistical results of the models (Model 1, Model 2, and Model 3). To test for autocorrelation in the fixed effects and random effects models, we employed the Durbin Watson (DW) autocorrelation tests of Bhargava, Franzini and Narendranathan, and the Baltagi–Wu (LBI) autocorrelation tests of Baltagi and Wu. Durbin Watson, and Baltagi – Wu autocorrelation tests were not determined as a critical statistic, but according to the literature, if the statistics are less than 2 it indicates the presence of autocorrelation. If there are heteroscedasticity and autocorrelation in the models, the standard errors must be corrected (to obtain robust standard errors) before the parameters can be estimated. Nonparametric heteroskedasticity autocorrelation (HAC) is based on the cross-section averages and has been suggested by Driscoll & Kraay (1998). HAC standard errors are robust to heteroskedasticity, serial correlation and spatial correlation. Furthermore, for Model 2, the estimators developed by Arellano (1987), Froot (1989), and Rogers (1993), which ensure robust parameter estimates in the case of autocorrelation and heteroscedasticity, were utilized. This estimator enables the computation of so-called Rogers or clustered standard errors. If this estimator allows intragroup correlation to be utilized, the estimates done with pooled standard errors will be robust. This estimator affects the estimated standard errors and variance – covariance matrix of the estimators (VCE). Nonetheless, it does not have an impact on the estimated coefficients (Yıldırım et al., 2020).

Table 7. Panel Regression Results (Model 1)

Dependent Variables: Z'' score						
Variable	Estimation of Coefficient	Driscoll-Kraay Standard Error	t	p-value	[%95 Confidence Interval]	
STD	5.298708	8.32429	0.64	0.5270	-11.3581	21.9555
TA	6.006048	4.30958	1.39	0.1690	-2.61741	14.6295
PR	4.347249	1.39049	3.13	0.0030	1.564881	7.12961
CFR	0.413138	0.17913	2.31	0.0250	0.054693	0.77158
FS	19.53423	7.83541	2.49	0.0150	3.855630	35.2128
CR	5.453615	1.80672	3.02	0.0040	1.838366	9.06886
LR	-0.66363	0.34993	-1.9	0.0630	-1.36386	0.03659
C	-137.225	54.8060	-2.5	0.0150	-246.891	-27.558
R-Square: 0.3335			Sample Period: 2004Q1-2018Q4			
F-Statistics: 17.63			Cross-Section No: 35			
Prob (F- Statistics): 0.0000			Observations: 2100			

Table 7 consists of the estimates computed to test the determinants of Altman's Z-score financial distress prediction. The result of the analysis indicates that profitability ratio (PR), cash flow ratio (CFR), firm size (FS) and current ratio (CR) are positively related to Altman's Z-score. In other words, these variables have a positive effect on Altman's Z-score and a negative effect on the probability of bankruptcy. However, it was found that leverage ratio (LR) has a significant and negative association with Altman's Z-score. This means that the increase in leverage ratio (LR) increases the probability of bankruptcy of the airlines.

Table 8. Panel Regression Results (Model 2)

Dependent Variables: S-score						
Variable	Estimation of Coefficient	Std. Err.	t	p-value	[%95 Confidence Interval]	
STD	-11.17932	3.212345	-3.48	0.0010	-17.47540	-4.88324
TA	0.6807567	1.519916	0.45	0.6540	-2.298224	3.659737
PR	1.9808140	0.615596	3.22	0.0010	0.7742669	3.187361
CFR	0.2659457	0.202882	1.31	0.1900	-0.131695	0.663587
FS	0.7124655	0.350828	2.03	0.0420	0.0248544	1.400077
CR	0.0251389	0.798831	0.03	0.9750	-1.540539	1.590817
LR	0.0418542	0.026908	1.56	0.1200	-0.010884	0.094593
C	-2.892807	2.450858	-1.18	0.2380	-7.696401	1.910787
R-Square: 0.1994			Sample Period: 2004Q1-2018Q4			
Wald chi2 (7): 40.86			Cross-Section No: 35			
Prob > chi2: 0.0000			Observations: 2100			

Table 8 is composed of the estimates computed to test the determinants of Springate's Z-score prediction of bankruptcy model. The result of the empirical analysis shows that profitability ratio (PR) and firm size (FS) revealed a positive relationship and a significant connection with Springate's Z-score. When Springate's Z-score increases, the companies' probability of bankruptcy decreases, there is a negative relationship between the probability of bankruptcy score and bankruptcy risk.

Table 9. Panel Regression Results (Model 3)

Dependent Variables: J-score						
Variable	Estimation of Coefficient	Driscoll-Kraay Standard Error	t	p-value	[%95 Confidence Interval]	
STD	4.848078	0.7982601	6.07	0.0000	3.250764	6.445393
TA	1.489774	0.4637787	3.21	0.0020	0.561754	2.417793
PR	-0.34368	0.1261934	-2.72	0.0080	-0.59620	-0.09117
CFR	-0.21911	0.0882686	-2.48	0.0160	-0.39574	-0.04249
FS	-0.10281	0.0895986	-1.15	0.2560	-0.28209	0.076476
CR	-0.20484	0.1418311	-1.44	0.1540	-0.48865	0.078954
LR	0.011360	0.0117201	0.97	0.3360	-0.01209	0.034812
C	-1.24290	0.7366908	-1.69	0.0970	-2.71702	0.231206
R-Square: 0.1762			Sample Period: 2004Q1-2018Q4			
F-Statistics: 45.78			Cross-Section No: 35			
Prob (F- Statistics): 0.0000			Observations: 2100			

Table 9 consists of calculated estimates of factors affecting Zmijewski J-score. From the regression result, short term debt ratio (STD) and tangible assets (TA) have a significant and positive association with Zmijewski's J-score at the 1% level. Nevertheless, profitability ratio (PR) and cash flow ratio (CFR) are inversely related with Zmijewski's J-score. Therefore, the findings show that the short-term debt ratio (STD) and tangible assets (TA) decrease the probability of bankruptcy, while the ratio of profitability (PR) and cash flow ratio (CFR) increase it.

5. CONCLUSION

The air transport industry is one of the sectors that are most affected by the Covid-19 pandemic. The effect of the pandemic on airlines will be fully understood in the future, but the industry is now trying to evaluate which airlines will be affected more. Due to Covid-19, the issue of which airlines will have more financial damage and difficulty competing concerns both the investors and internal/external stakeholders of airlines. In this study, we focused on the financial factors that affect the probability of financial failure of the airlines by using their secondary financial data. In this study, we would associate the financial risk of airlines with the Covid-19 process from the following perspective. In the first stage, we identified financial indicators that may increase financial risk in the airline industry through the literature. In the second stage, we reveal that the financial distress, and bankruptcy risk of airlines increased in the Covid-19 process. In the third stage, we disclosed financial indicators that affect financial risk. In the final stage, we have revealed with the analysis results which financial indicators investors, shareholders and other players should focus on in the airline industry.

The analysis findings in this study contain valuable information as we have outlined which financial ratio most affects the probability of airline bankruptcy. Through the analysis of the financial statements of the airlines in detail, it may be viewed which airline is more probable to have financial distress. The findings are as follows.

- There is a positive relationship between the profitability ratio and the probability of bankruptcy score, which implies that as the airlines' profitability ratio increases, the probability of financial difficulties decreases. However, in model 3, this relationship is opposite and contrary to the hypotheses.
- There is a positive relationship between the cash flow ratio and the probability of bankruptcy score in model 1, but the cash flow ratio is inversely related to the probability of bankruptcy score in model 3. While calculating the bankruptcy probability score in the financial distress prediction models, different financial indicators and coefficients were used for each model. This may be the reason for the difference between the models on the effect of cash flow ratio on the probability of bankruptcy score.
- For Model 1 and Model 2, there is a positive relationship between the firm size and the probability of bankruptcy score. This relationship is significant and has a positive association at a level of 5%.
- The current ratio has a positive relationship with the probability of bankruptcy score. This implies that an increase in the level of current assets or consistent cash flows in airlines will lead to a decrease in the possibility of financial failure or bankruptcy risk.
- There is a negative relationship between the leverage ratio and the probability of bankruptcy score. This implies that a decrease in the debt levels of airlines increases the possibility of financial failure or bankruptcy risk and vice-versa for all airlines.
- According to the findings of Model 3, there is a negative relationship between the short term debt ratio and the probability of bankruptcy score. However, this finding is contrary to our theoretical expectations.
- It was found that tangible assets have a significant and positive association with the probability of bankruptcy score. This is related to the number of aircraft in the fleet and firm size of the airlines and is in line with theoretical expectations.

Many airlines halted their operations due to the Covid-19 global pandemic. Airlines whose cash flows deteriorate are at risk of financial distress and/or bankruptcy. As mentioned earlier, we focused on the financial performance indicators of airlines that affect the probability of bankruptcy. In other words, we analyzed which financial variables increased or decreased the risk of bankruptcy in the airline industry. The findings may provide clues that predict the potential impact of the Covid-19 pandemic on airlines. The size of the impact can be determined by examining the financial statements of the airlines. Therefore, by examining the financial rates of the airlines, it can be determined which airlines have a risk of bankruptcy.

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