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Bankruptcy prediction for the European aviation industry: An application of the Altman model

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Abstract

Aviation industry is extremely vulnerable to economic turbulence or a pandemic. Over the past decade, a number of well-known European airline brands have gone into bankruptcy, with consequences such as leaving thousands of passengers stranded abroad. The present research assesses the predictive power of the updated Altman *Z*-score model (1983 and 2017) using data on European airline bankruptcies over the period 2009–2020. The results indicate that the *Z*″-score (2017) for private non-manufacturing companies shows satisfactory predictive power when applied on European aviation industry. In this study, we analyze in depth the performance of the updated Altman *Z*′- and *Z*″-scores (1983, 2017), connecting airline's financial and non-financial information, and provide a comprehensive interpretation of *Z*-score predictive power. We aim to contribute to the literature by offering a unique and novel perspective on the Altman model's accuracy for the European air transport industry.

JEL CLASSIFICATION
G33, G34, G38, M21, M41

1 | INTRODUCTION

The European airline industry is highly fragmented (IATA, 2019; Smit, 1997). Most members of the European Union consider it important to have a national air carrier. In consequence, it takes more city pairs to generate revenues and more airlines share the profit, as opposed to a less fragmented market like North America. Nevertheless, according to IATA (2019), the Big Four airlines in Europe (Lufthansa, IAG, Air France-KLM, and Ryanair) accounted for over half of the profit of the whole industry, leaving the other medium- and small-size European airlines in an even more difficult situation.

That explains why, although the European aviation business has a good industry-level profit, there has been a series of bankruptcy or merger events over the last decade. Air Berlin, the second-largest German airline, filed for insolvency in 2017 after consecutive losses. Monarch, a sizeable British airline company that collapsed in 2017, was the second largest to ever suspend trading in UK history. Subsequently, the largest UK airline collapse event took place in 2019, when Thomas Cook announced bankruptcy and ceased operations, leaving hundreds of thousands of tourists stranded around the world. The COVID-19 left global airlines struggling for survival (Budd et al., 2020; Kaffash & Khezrimotlagh, 2022). Air transportation industry occupies a small share of GDP but is closely connected with activities of many other sectors. It has a great impact, on one hand, on some upstream sectors like support activities to air transportation and operation of airports and, on the other hand, on several downstream sectors like trading of goods and offering movement services for natural persons. Bankruptcies or merger events among airline companies could have a negative effect on competition in the market and consequently lead to possible repercussions on prices (OCED, 2020). Up to April 2020, the influence of COVID-19 on air traffic is estimated to put around 6.7 million jobs at risk and cause a negative impact on GDP of $452 billion across Europe. The increasing risk of high unemployment and lower GDP raised great concern of bankruptcy prevention of European air carriers (IATA, 2020).

Rescue measures given the pandemic situation are different in European countries. Some schemes were open to all airlines, while in other countries, bailout aids were basically given to the national flag carriers. It is indicated that such distinctive support policies may lead to a possible regression in the liberalization process of the European airline market since it is harmful for promoting competitiveness and effectiveness (O'Leary, 2020).

Since airline failure has a great impact on tourism and transportation activities, bankruptcy prediction is very important for policymakers, management, and investors. Over the past 50 years, bankruptcy prediction has been a field of increasing interest to researchers all around the world. Many academic studies have looked for higher accuracy prediction models. Despite a large body of research focusing on the prediction of corporate financial distress, the breakthrough model in the bankruptcy prediction field, Altman's (1968) *Z*-score model, remains relevant (Altman, 1968, 1983, 2017).

In summary, based on our knowledge, there is a lack of prior research that has evaluated predictive performance of the updated Altman *Z*-score model (1983, 2017), specifically for European air carriers. In the literature, the majority of studies focused on US airline financial distress and Altman *Z*-score (1968) are mostly applied (Alan & Lapré, 2018; Davalos et al., 1999; Gritta, 1982; Lu et al., 2014; Ribbink et al., 2011; Stepanyan, 2014). While previous studies have utilized the Altman *Z*-score model for European airlines (Shi et al., 2023; Shi & Li, 2021), a comprehensive analysis of its predictive power has been lacking. To address the existing gap in the literature regarding the accuracy of updated *Z*-score models on European airline companies, in this present study, we assess the predictive capacity of the updated Altman models as applied to European air carriers. We aim to contribute to the literature by focusing on a comprehensive interpretation of updated *Z*-score's performance and offering a unique and novel perspective on the updated *Z*-score model's predictive power in the European air transportation industry.

The paper is organized as follows. Section 2 starts with a literature review of principal bankruptcy prediction models and identifies the application of the Altman *Z*-score model in aviation industry. Our research methodology is presented in Section 3. Section 4 gives a descriptive analysis of sample. The analysis of *Z*-score and main research findings are discussed in Section 5. We finish in Section 6 with conclusions, limitations, and future research.

2 | LITERATURE REVIEW

Bankruptcy prediction has been a subject of research since 1932 when Fitzpatrick published a study comparing failed and successful firms. In this study, 13 financial ratios were interpreted, accompanied by multiple variable analysis (FitzPatrick, 1932). In 1966, a univariate analysis was used for examining the predictive ability of ratios. The results show that predictive performance would have been better if multi-ratio analysis had been used (Beaver, 1966). The first multivariate analysis, the so-called *Z*-score, was published 2 years later by Altman (1968). It is a five-factor Multivariate Discriminant Analysis (MDA) model that was claimed to be able to correctly predict the bankruptcy of 95% of public manufacturing firms 1 year prior to failure (and 72% 2 years prior). In 1983, Altman re-completely estimated the original model and proposed a Z'-score model for private firms which substituted market value for the book value of equity. He also presented a four-variable Z''-score model which excluded the sales/total assets ratio, claiming that it could predict bankruptcy for private and public manufacturing and non-manufacturing firms. Altman et al. (2017) applied the Z''-score to 31 European companies and three non-European countries, concluding that this model performs very satisfactorily in an international context.

A large body of research has focused on the prediction of corporate financial distress, and different methods have been applied in the literature. MDA and Logistic Regression/Logit have been widely applied. Some scholars claimed that the discriminant approach showed predictive capacity with 96% accuracy 2 years prior to failure (Deakin, 1972). Logit models are also found to achieve good performance (Dambolena & Shulman, 1988), while the mixed logit model was stated to outperform the standard one (Jones & Hensher, 2004). Other methods for bankruptcy prediction include probit (Ahmadpour Kasgari et al., 2012; Kovacova & Kliestik, 2017), hazard model (Dang, 2013; Eling & Jia, 2018; Tudor et al., 2015), and partial least squares (Ben Jabeur, 2017; Serrano-Cinca & Gutiérrez-Nieto, 2013). Artificial intelligence techniques are also employed in the field of bankruptcy prediction. Neural networks have been the primary method used in bankruptcy prediction studies since the 1990s (Gissel et al., 2007). There are other intelligence techniques such as support vector machine (Lee et al., 2012; Li et al., 2014), decision tree (Chen, 2011; Kim & Upneja, 2014), and case-based reasoning (Li & Sun, 2008; Park & Han, 2002).

In the airline industry, a review of bankruptcy prediction studies and the application of various models to US air carriers was published by Gritta et al. (2006). It mentioned two airline industry-specific models: the Airscore (Chow et al., 1991) and the Pilarski or P-score (Pilarski & Dinh, 1999). Airscore used an MDA approach, which is similar to the *Z*-score but is restricted to airline industry data. It reports accuracy rates between 76% and 83%. However, according to Gritta et al. (2006), one of the pioneers of the Airscore model, it can be biased toward the bigger size carriers in the sample. P-score is a logistic regression model that estimates the probability of bankruptcy of an air carrier. It borrowed three ratios from the Altman *Z*-score. Some authors considered that the P-score model is correlated to the Altman *Z*-score when applying to major carriers in the United States (Goodfriend et al., 2004).

Z-score, as a generic model, is widely used in predicting bankruptcy in the aviation industry (Chung & Szenberg, 2012; Golaszewski & Saunders, 1992; Gritta, 1982; Gritta et al., 2011; Kolte et al., 2018; Scaggs & Crawford, 1986; Stepanyan, 2014). Gritta

(1982) applied the Z-score to nine US air carriers, comparing their 1978 (a year of increasing profit) and 1981 (a year of financial difficulties) values. He declared that Z-score reflected the different situations and successfully predicted their insolvencies. Together with other authors, he published an updated study on airline financial condition and insolvency prediction which applied the Altman Z-score (Gritta et al., 2011), stating that "Z-score perhaps is the most popular approach to track financial health and the potential for insolvency." They calculated Z values for 15 US air carriers during the 1997–2006 period and concluded that 14 of these carriers had experienced a decline in their financial health. Other authors applied the Z-score to Indian airlines (Kolte et al., 2018). They state that the Z-score was able to predict satisfactorily the corporate financial distress of airlines in India and recommend Indian banks, shareholders, and financial institutions to use it as a tool for predicting potential bankruptcy.

Most studies show low Z-score values in US airline industry. Analysis carried out by Scaggs and Crawford (1986) emphasized the importance of the debt position as a significant factor in the Altman Z-score model. It is, in fact, common that debt financing constitutes a high percentage of an airline's financing structure, bringing consequently high-interest payments. In fact, many US air carriers can maintain operations with Z-score values lower than normal over a long period (Golaszewski & Saunders, 1992). A modified cut-off, significantly lower than the original Altman's, was proposed: scores below 1.0 indicate a need for concern, and scores below 0.5 display financial distress. Other studies showed low Z-scores in US airlines during the years 1982–1989 (Chung & Szenberg, 2012) and 2007–2012 (Stepanyan, 2014).

In regard to more recent airline industry bankruptcy prediction studies, scholars tend to identify key ratios as performance indicators for air carriers. Mahtani and Garg (2018) identified six categories of internal and external key factors of financial distress in the Indian aviation industry. They stated that financial factors are the most critical category and have a major influence on air carriers' business stability. There are other studies of the relationship between operational and financial performance in the airline industry. For example, Alan and Lapré (2018) identified a set of operational variables, from four performance areas, and assessed their predictive power—however, with only 20 bankruptcy filings, this was not large enough to develop a forecasting model to measure its out-of-sample forecast accuracy.

In the literature, the majority of studies focus on US airline financial distress (Alan & Lapré, 2018; Davalos et al., 1999; Gritta, 1982; Lu et al., 2014; Ribbink et al., 2011; Stepanyan, 2014). The Chapter 11 bankruptcy protection allows the US airlines to organize and restructure, by providing debtors with possible reorganization plan maintaining the business in running and paying creditors according to a renegotiated schedule. It helps US airlines when competing with other non-US airlines more successfully (Bock et al., 2019). The EU Restructuring Directive offers firms with a higher efficiency of procedures in aspects of restructuring, insolvency, and discharge of debt. However, the significance of such insolvency law cannot be overstated. Some argue that this is due to the member states of the EU that are more likely to have overprotective behavior on the regulation of sensitive policy like insolvency (Ghio et al., 2021). On the contrary, the United States has achieved more consensus of its member states toward the Chapter 11. To the best of our knowledge, no evaluating studies for financial distress prediction model exist for European airlines; there are only comparative analyses and some individual case studies. Previous European studies focus on aspects such as comparison of efficiency and productivity between Europe and the United States (Assaf & Josiassen, 2012), competitive position at network level (Maertens, 2018), and the effects of competition on price dispersion in European airline markets (Obermeyer et al., 2013). Some authors analyzed the determinants of financial distress in the European airline industry (Shi & Li, 2021). They studied the interaction effect of flagship with the relationship between financial-related factors and the degree of financial distress measured by the Altman Z-score. However, the accuracy of the Z-score model applied on the European airline industry has not been explored. Other studies analyze individual cases of airlines in Europe, but not from a financial perspective: the effects on consumer welfare after bankruptcy of the Hungarian airline Malév (Bilotkach et al., 2014), the value proposition-based strategy of Ryanair (Thomas, 2015), the strategic evolution of re-engineering Aer Lingus (O'Connell & Connolly, 2016), the condition and strategies driving aviation performance using Italian airport data (Giovanelli & Rotondo, 2022), and the customer loyalty programs of Air Berlin (Zakir Hossain et al., 2017).

To conclude, to the best of our knowledge, no previous studies have assessed the predicting performance of the Altman Z-score model on European air carriers. Given the difficult situation that European airlines have been struggling with in times of austerity, as well as the importance of this research topic, the present study represents a worthwhile contribution to the literature. Additionally, we apply the updated Z'-score (1983) and Z''-score (2017) models to European airlines that went bankrupt in the 2009–2020 period, verify the predictive capacity of each, and compare model performance.

3 | METHODOLOGY

Based on the previously cited literature, we first adopt the Altman Z' model (Altman, 1983) for our study. The formula and zones of discrimination are presented as below:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5.$$

where X_1 = Working Capital/Total Assets (WCTA);

X_2 = Retained Earnings/Total Assets (RETA);
X_3 = Earnings before Interest and Taxes/Total Assets (EBITTA);
X_4 = Book Value of Equity/Book Value of Total Liabilities (BVETD);
X_5 = Operating revenues/Total Assets (ORTA);
Z' = Overall Index.

Zones of discrimination:

$Z' > 2.9$—"Safe" Zone (very low possibility of going bankrupt)
$1.23 < Z' < 2.9$—"Gray" Zone (or the ignorance zone)
$Z' < 1.23$—"Distress" Zone (high possibility of going bankrupt)

Continuing with bankruptcy models, we then apply the Altman Z''-score model, since Altman et al. (2017) concluded that the Z''-score model performs very satisfactorily in an international context. Unlike the original Z-score model, which is for publicly traded manufactures, Z'-score is claimed to be suitable for private manufacturing firms and Z''-score may be more widely applied for private and public manufacturing and non-manufacturing firms.

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4.$$
$$Z''\ (\text{for emerging market}) = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4.$$

where X_1 = Working Capital/Total Assets (WCTA);

X_2 = Retained Earnings/Total Assets (RETA);
X_3 = Earnings before Interest and Taxes/Total Assets (EBITTA);
X_4 = Book Value of Equity/Book Value of Total Liabilities (BVETD);
Z'' = Overall Index.

Zones of discrimination:

$Z' > 2.6$—"Safe" Zone (very low possibility of going bankrupt)
$1.1 < Z' < 2.6$—"Gray" Zone (or the ignorance zone)
$Z' < 1.1$—"Distress" Zone (high possibility of going bankrupt)

In this paper, we decide to apply both the Z'-score (1983) and Z''-score (2017) to obtain more complete results by allowing their performance to be compared.

3.1 | Sample construction

This study covers European airline companies that went bankrupt during 2009–2020 and active airlines that have available data for the last 10 years (2011–2020). The accounting and financial data required for applying the Z-score model were obtained from two databases: Amadeus and SABI (Sistema de Análisis de Balances Ibéricos/Iberian Balance Sheet Analysis System). Amadeus is a pan-European database that, at the moment of sampling, contains financial information on over 24 million public and private companies. SABI contains financial information on Spanish and Portuguese companies.

Several requirements are set for data sampling. First, the firm should have specific accounting data for calculating Z-score: total assets, working capital (current assets–current liabilities), retained earnings, EBIT, book value of equity, book value of total liabilities, and operating revenue. Second, the firm should have available data for at least 3 years prior to the bankruptcy to obtain better observation of changes in the Z-score values. Third, we require that the firms selected had failed during the 2009–2020 period. After screening the availability of data from these databases, 17 bankrupted airlines were obtained for our dataset. Although some airlines were later acquired or merged into other companies, they had been in critical financial distress and gone into bankruptcy in the first place. Additionally, companies such as Thomas Cook and VIM that went bankrupt due to administration or issues related to board of management rather than financial problems are also included. For comparison analysis, we construct another sample of 17 European active airlines using the Amadeus database, with the requirement that they should have specific accounting data for calculating updated Z-score models for the last 10 years.

We ranked the airlines according to the average operating revenue. This value ranges from 6 million to 3658 million euros. The operating age ranges from 3 to 73 years. The complete ranking of the bankrupted airline list is shown in Table 1.

4 | DESCRIPTIVE ANALYSIS OF SAMPLE

To better understand the main variables of the models under study, a descriptive analysis is carried out. The analysis contains changes in Working Capital, EBIT, Debt to Assets (D/A) ratio, and a global analysis of variables. In terms of liquidity measurement, Working Capital is shown to have better statistical significance than current ratio and quick ratio and it is stated to be the best indicator of ultimate discontinuance (Altman, 1968). EBIT has the highest coefficient in the Z' and Z'' models (3.107 and 6.72). It shows that a firm's true earning power is often related closely to corporate failure. D/A ratio, as one of the measurements of financial risk, examines the degree of financial leverage employed (Capobianco & Fernandes, 2004; Guzhva & Pagiavlas, 2003).

4.1 | Working capital changes

Working capital represents the difference between current assets and current liabilities. It measures a company's liquidity and operational efficiency. Low working capital indicates a risk of financial distress or bankruptcy.

Figure 1 shows trends in the airline companies' working capital for several years prior to the failure (depending on data availability). The X-axis represents the number of years before bankruptcy. For example, year 5 indicates 5 years prior to bankruptcy, and year 0 represents the last year available. Two vertical axes divide two groups of airlines according to their size. The left-hand-side vertical axis side corresponds to smaller airlines (Niki, VIM Airlines, Germania, Aigle Azur, Clickair, Air Comet, Flybmi, Openskies, Islas Airways, Quantum Air, and Helitt), and that on the right side corresponds to larger ones (Air Berlin, Transaero, Thomas Cook, Spainair, Monarch, and Aerosvit Airlines). As can be seen, most airlines show constant negative or near-zero working capital except for Thomas Cook Airlines and VIM. Big airlines such as Transaero, Spainair, Air Berlin, and Aerosvit had constant and declining negative working capital for

TABLE 1 Ranking by average operating revenue of European airlines that went bankrupt from 2009 to 2020.

	Company name	Country	Period	Duration (year)	Operating revenue (euro, average)
1	Air Berlin	Germany	1978–2017	39	3,658,758,000
2	Transaero	Russia	1991–2015	24	1,376,767,000
3	Thomas Cook Airlines Limited	UK	2003–2019	16	1,242,222,000
4	Spanair	Spain	1986–2012	26	927,730,000
5	Monarch Airlines	UK	1967–2017	50	804,286,902
6	Niki	Austria	2003–2017	14	455,814,000
7	Aerosvit Airlines	Ukraine	1994–2013	19	382,887,000
8	Aigle Azur	France	1946–2019	73	308,292,898
9	Germania	Germany	1989–2019	30	301,738,000
10	Clickair	Spain	2006–2009	3	233,630,000
11	VIM Airlines	Russia	2000–2017	17	204,472,000
12	Air Comet	Spain	1997–2009	12	184,475,119
13	Flybmi	UK	1987–2019	32	86,333,911
14	Openskies	France	2008–2018	10	65,691,544
15	Islas Airways	Spain	2001–2012	11	28,499,238
16	Quantum Air	Spain	1999–2010	11	24,583,670
17	Helitt Líneas Aéreas	Spain	2009–2014	5	6,224,353

Source: Amadeus and SABI database, elaborated by authors.

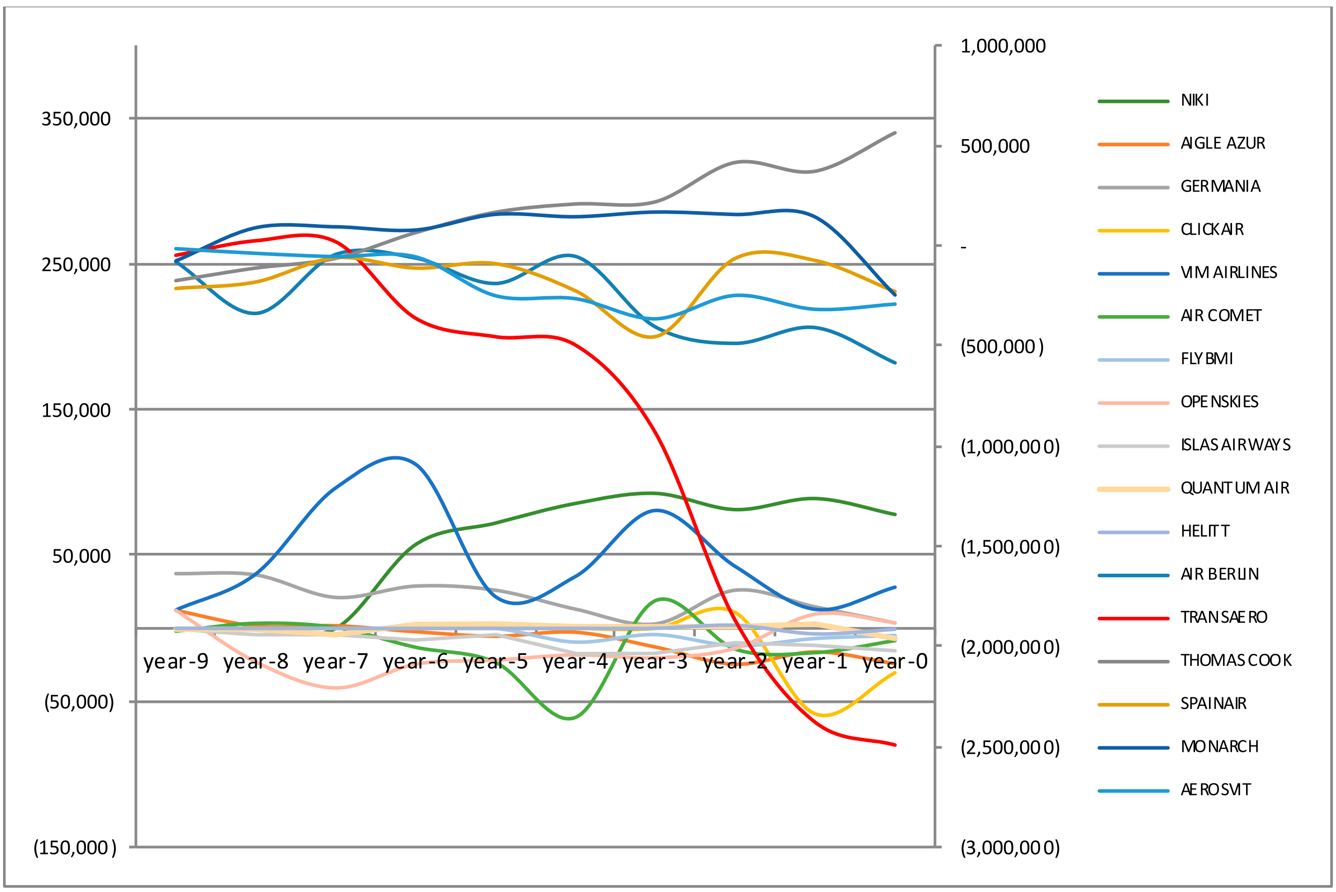

FIGURE 1 Working capital changes (Euro, in '000). *Source*: Amadeus and SABI database, elaborated by authors.

the last 10 years before failure. Transaero, especially, had a dramatic decline in working capital during the last 10 years, from 250 million euros to −2400 million euros. Some small airlines display volatile working capital changes such as VIM Airlines, Air Comet, and Openskies.

4.2 | EBIT changes

EBIT (earnings before interest and taxation) measures a firm's profit including all operating and non-operating incomes and expenses except interest and tax. It is used for analyzing the performance of a company's core operations, without considering the cost of capital structure and tax expenses.

In Figure 2 (as in Figure 1), the *X*-axis represents the number of years before bankruptcy. Two groups of airlines are divided by two vertical axes according to the size. The left-hand-side vertical axis side corresponds to the same 11 smaller airlines (Niki … Helitt), and that on the right side corresponds same six larger ones (Air Berlin, …, Aerosvit Airlines). As can be seen, many companies such as Air Berlin, Transaero, Spanair, Monarch Airlines, Air Comet, Openskies, and Flybmi were all struggling with negative EBIT for years before the final failure. Air Berlin had a negative EBIT reaching −670 million euros during its last year of operation. Germania, Aigle Azur, Quantum Air, Islas Airways, and Helitt had been struggling with EBIT close to zero before the ultimate failure. Aerosvit Airlines and Clickair were at loss for the last few years before finally going into bankruptcy.

4.3 | Debt to assets ratio

There are several ratios for estimating financial leverage and to seeing the capital structure of a firm. Our initial preference had been to use debt to equity ratio (D/E ratio); however, after calculating the D/E ratio for the air carriers in our sample, these were mainly negative since airlines close to bankruptcy often show negative equity figure in the balance sheet. Guzhva and Pagiavlas (2003) indicated that a negative D/E ratio makes little practical sense when evaluating financial leverage. It is clear that, for the purpose of measuring financial leverage, a negative D/E ratio tends to indicate that the value of the company is negative and visually it is more complicated to compare one negative D/E ratio with another negative D/E ratio to see the degree of financial leverage. We adopted the solution of Guzhva and Pagiavlas (2003) and considered debt to assets ratio (D/A ratio) instead in order to see the degree to which a company has used debt rather than equity to finance its assets. A high D/A ratio indicates a high degree of leverage and thus high financial risk. A D/A

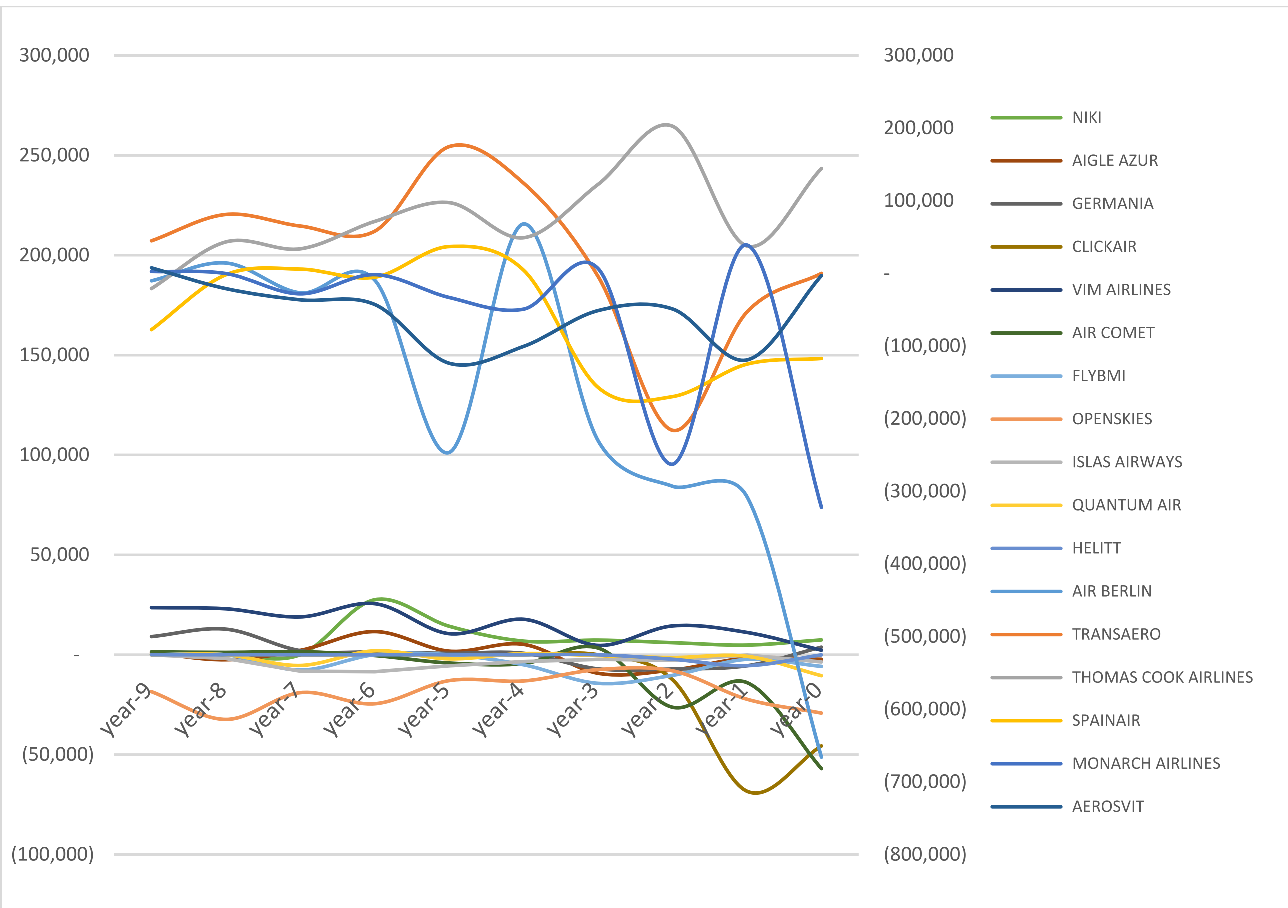

FIGURE 2 EBIT changes (Euro, in '000). *Source*: Amadeus and SABI database, elaborated by authors.

ratio greater than 100% shows more liabilities than assets which implies that the firm may face a considerable risk of being defaulted on its debt.

As a highly capital-intensive and highly leveraged industry, aviation tends to have high D/A ratios and we display ratio trends for the 17 bankrupt airlines in our sample (see Figure 3).

The majority of sample airlines show D/A ratios higher than 100%. Aerosvit Airlines, Openskies, and Spanair show significantly high D/A ratios reaching 470%, 327%, and 268%, respectively. Other airlines like Air Berlin, Transaero, and Monarch Airlines had ratios close to 200%. All these are significantly beyond the optimum range of financial leverage for airlines which is believed to be between 40% and 77% (Capobianco & Fernandes, 2004). Guzhva and Pagiavlas (2003) also found that US airline Pan American had an increasing D/A ratio and reached 205% before it went into bankruptcy, which implies that a high D/A ratio might cause insolvency before the actual bankruptcy.

4.4 | Analysis of variables

Variables included in this study are analyzed in terms of maximum value, minimum value, average value, and standard deviation (see Table 2). X_1 = Working capital/total assets measures the liquidity. X_2 = Retained earnings/total asset is the profitability ratio. X_3 = EBIT/total assets evaluate the productivity of a firm. The average values of these three variables of data set are negative, indicating that the sample shows severe problems in liquidity, profitability, and productivity. X_2 has the highest standard deviation: 2.5, revealing a large difference between maximum and minimum values. X_5 = sales activity of a firm. The data set shows a good average value of this variable, implying that although firms were bankrupted, their capital turnover and sale-generating ability were still sound.

TABLE 2 Descriptive analysis of variables.

		Max	Min	Average	St. De
X_1	WC/TA	0.982	−11.904	−0.502	1.8
X_2	RE/TA	0.976	−13.327	−0.905	2.5
X_3	EBIT/TA	0.223	−4.474	−0.226	0.5
X_4	EQ/TL	1.318	−0.930	0.018	0.4
X_5	OR/TA	7.829	0.00003	2.195	1.5

Source: Amadeus and SABI database, elaborated by authors.

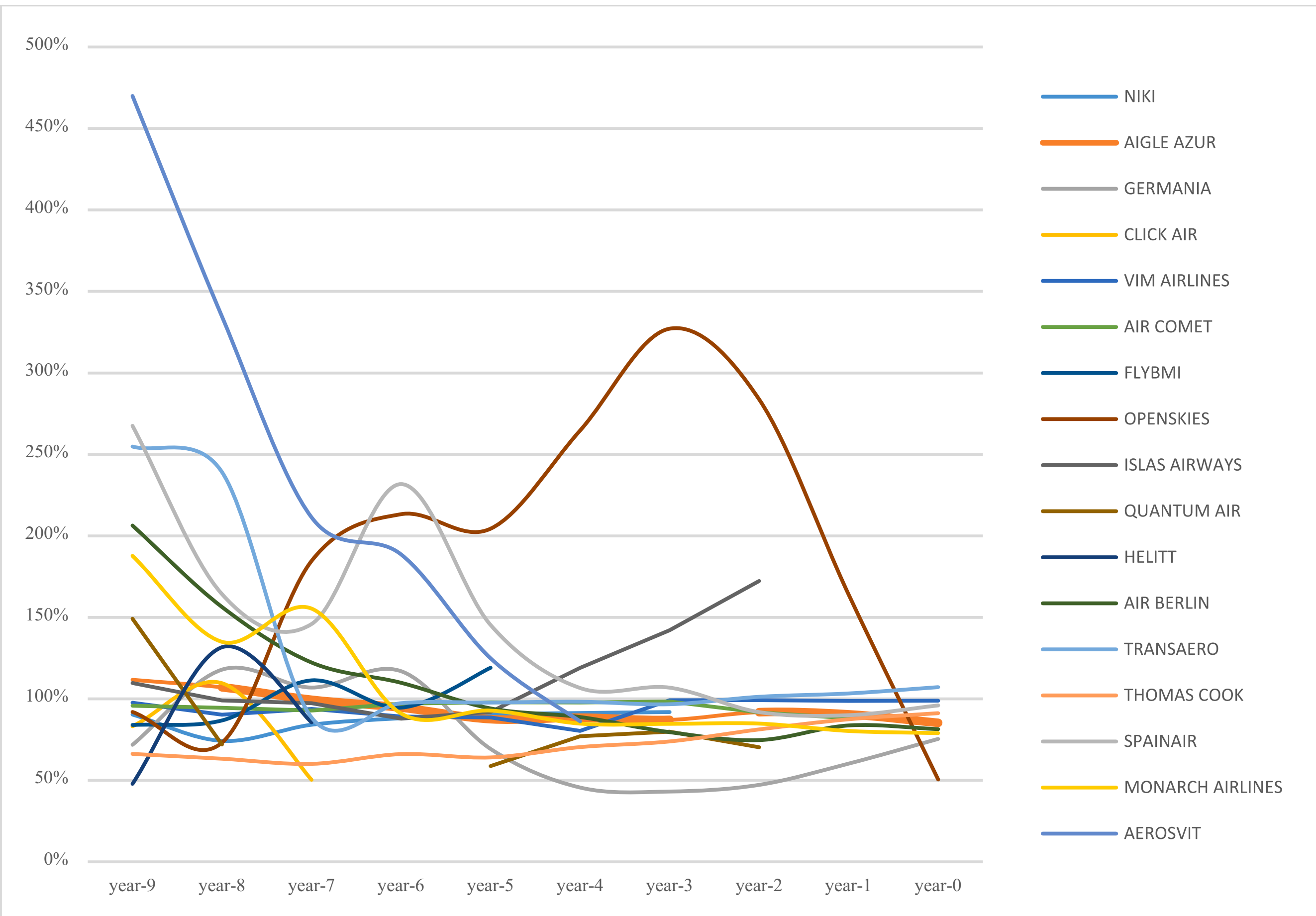

FIGURE 3 Debt to assets ratio changes for sample companies. *Source*: Amadeus and SABI database, elaborated by authors.

5 | ANALYSIS RESULTS OF *Z*-MODELS AND DISCUSSIONS

We applied the *Z*′-score (1983) and *Z*″-score (2017) models (*Z*″-score emerging for emerging markets such as Russia and Ukraine) on 17 selected bankrupt airline companies and obtained corresponding results (see Figure 4). For better visualization, we classify the results into three different color zones: "Safe" (green), "Gray" (gray), and "Distress" (red). During the analysis period (from 2001 to 2018), the time frame for each airline company ranged from 3 to 10 years due to the available of data. For example, Quantum Air had missing data for long-term debt during the years 2005–2006; therefore, the corresponding results of the *Z*-score were not available for these 2 years.

In this section, we first compare our results with previous airline bankruptcy prediction studies that used *Z*-score models. Then, we compare the performance of *Z*′-score (1983) and *Z*″-score (2017) based on our sample of bankrupt airlines. Although some previous studies that we used for comparison applied the original *Z*-score (which is for publicly traded companies), the classification results are comparable with results obtained from our study.

The first observation is that the majority of airlines show *Z*′ and *Z*″ values in the gray or the distress (red) zones prior to the failure, which aligns with the results obtained by other previous studies (Chung & Szenberg, 2012; Gritta et al., 2011; Kolte et al., 2018; Stepanyan, 2014). Gritta et al. (2011) analyzed 15 US major carriers and found that the majority of airlines were within the distress zone during 1997–2006. Chung and Szenberg (2012) analyzed the financial performance of seven major US airline companies during 1982–1991 and stated that none of them had *Z* values in the healthy zone. Stepanyan (2014) calculated the *Z*-score for seven US legacy air carriers and indicated that all of them had *Z* values in the distress zone for six consecutive years from 2007 to 2012. Kolte et al. (2018) calculated the *Z*-, *Z*′-, and *Z*″-scores for the bankrupted Indian airline Kingfisher during the period 2008–2013 and stated that all three were in the distress zone, showing strong signs of insolvency up to 6 years prior to failure.

MODEL/COMPANY	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Air Berlin																		
Z' score								1.562	1.642	1.810	1.608	2.205	1.555	1.278	1.383	-0.200		
Z'' score								-0.163	0.958	0.710	-0.815	0.265	-2.711	-3.749	-5.622	-10.097		
Transaero																		
Z' score							1.769	1.870	1.887	1.665	1.459	1.329	1.094	0.698	-2.267			
Z'' score emerg							2.694	3.088	4.363	3.989	1.899	2.462	2.326	0.502	-16.693			
Thomas Cook																		
Z' score									0.932	1.515	1.723	1.922	1.866	2.151	2.145	2.167	1.820	1.736
Z'' score									-1.313	-0.429	0.136	1.770	2.797	3.159	3.219	4.885	3.645	4.048
Spanair																		
Z' score		0.798	1.668	1.884	1.741	2.456	2.066	-0.543	-0.266	-0.058	-1.211							
Z'' score		-3.937	-2.722	-0.861	-2.339	-1.419	-5.840	-18.086	-8.776	-7.749	-17.300							
Monarch airlines																		
Z' score							1.562	1.915	1.650	1.823	1.838	1.775	2.541	0.037	1.917	-2.657		
Z'' score							0.145	2.003	1.562	1.763	2.447	1.640	2.929	-4.356	0.909	-14.035		
Niki																		
Z' score										1.689	1.861	2.168	2.556	3.032	4.534	6.403		
Z'' score										2.241	2.193	2.535	3.259	3.622	5.628	7.453		
Aerosvit airlines																		
Z' score							3.413	2.090	-0.221	0.113	-2.496	-1.637						
Z'' score emerg							3.306	-2.536	-9.164	-7.571	-27.939	-36.730						
Aigle Azur																		
Z' score							3.124	2.838	2.754	2.647	2.296	2.497	2.307	2.484	2.390	2.274		
Z'' score							1.421	0.143	0.419	0.893	0.204	0.538	-1.000	-2.050	-1.611	-2.448		
Germania																		
Z' score								4.115	4.983	6.079	7.383	6.344	7.305	7.228	5.076	4.635	2.153	
Z'' score								5.903	7.688	6.403	8.082	7.039	3.621	-1.233	0.636	-0.595	1.336	
Clickair																		
Z' score						0.327	-0.238	1.905										
Z'' score						2.212	-9.730	-2.647										
VIM airlines																		
Z' score							1.470	1.631	1.218	1.734	1.390	1.495	1.193	1.432	1.905	1.832		
Z'' score emerg							4.297	5.260	7.206	7.906	5.045	5.345	5.835	5.475	5.103	4.575		
Air Comet																		
Z' score	3.660	2.472	0.366	0.456	0.564	1.946	0.886	1.333	0.438									
Z'' score	1.374	0.624	-0.324	-1.014	-2.312	1.289	-1.284	-0.771	-1.418									
Flybmi																		
Z' score													1.569	1.118	1.608	2.071	1.595	
Z'' score													-4.210	-4.857	-6.685	-3.023	-3.211	
Openskies																		
Z' score									-0.182	-5.254	-5.613	-11.844	-6.588	-4.225	-4.923	-4.358	-4.478	-0.950
Z'' score									-3.014	-27.014	-36.963	-70.001	-43.193	-28.490	-37.440	-30.133	-19.161	-3.862
Islas airways																		
Z' score				-3.162	-1.918	-0.468	0.208	0.322	0.132	0.470	0.198							
Z'' score				-14.444	-14.108	-9.554	-5.394	-2.696	-2.541	-1.940	-2.815							
Quantum air																		
Z' score	-0.571	1.849	1.126	2.671	-	-	2.433	-2.106										
Z'' score	-3.776	1.478	0.196	1.485	-	-	0.610	-11.611										
Helitt																		
Z' score											-0.348	-1.089	0.140					
Z'' score											-0.231	-6.901	-1.944					

Distress zone Grey zone Safe zone

FIGURE 4 *Z*′ and *Z*″ results of bankrupted sample airlines. *Source*: Amadeus and SABI database, elaborated by authors.

Second, among results in the distress zone, a significant number of airlines show negative Z' and Z'' values. Negative results imply a critical financial situation for firms as they might have negative profitability, negative working capital, etc. (Gritta et al., 2011).

Regarding the comparison between the predictive performance of Z'- and Z''-scores, our main observations are as follows:

(a) Z''-scores are more sensitive predictors than Z'-score. Airlines like Air Berlin, Spanair, Aigle Azur, Germania, and Flybmi have Z'' values in the distress zone but Z' value in the gray or even safe zones. Meanwhile, airlines that have both Z' and Z'' values in the distress zones, Aerosvit Airlines, Air Comet, Openskies, Islas Airways, Quantum Air, and Helitt, show a lower Z' than Z''-score. (b) Contrary to (a), Thomas Cook and VIM Airlines show a Z' value in the gray zone while the Z'' value in the safe zone. This reflects the fact that the Z'-score may show better predictive performance than the Z''-score on airlines that were bankrupted not for insolvency but for other factors. (c) Regarding the three companies that have Z'' value in the safe zone during the last years prior to bankruptcy (Thomas Cook, Niki, and VIM Airlines), although the Z'-score has not classified them to distress zone either, it performs slightly better than the Z'', since the Z'-score displays lower values in all these three cases.

To discover more details of the predictive capacity of these two models, we summarized the results by dividing them into two groups: predicted group if a firm shows Z values in distress zone for at least 1 year prior to the declaration of bankruptcy, and unpredicted group if a firm did not show Z value in distress zone for at least 1 year prior to the declaration of bankruptcy (see Table 3).

Applying the Z'-score model, 11 of the 17 airlines were classified in the distress zone before bankruptcy. The remaining six airlines show values in gray zone or even safe zone, and the distressed financial situation of the company prior to the bankruptcy has not yet been revealed. Regarding Z''-scores, 14 of 17 airlines have been correctly classified as financially distressed companies. Three companies remain unsuccessfully predicted (Thomas Cook, Niki, and Vim Airlines), which aligns with the result of Z'-score, as neither model has classified them into distress zones. Two questions might be raised regarding the results: (a) why has the Z''-score classified more distressed airlines than the Z'-score and (b) why do neither the Z' nor the Z''-score predict bankruptcy for these three companies?

In order to understand (a), we disaggregate the calculation process of Z' and Z'' values, looking into each variable to see which ratio contributes the most to the result Z' and Z'' values for Germania, Aigle Azur, and Flybmi.

The main finding is that, in the Z'-score model, although X_3 (EBITTA) has a high coefficient (3.107) in assessing potential bankruptcy (Stepanyan, 2014), the X_5 (ORTA) has the strongest influence on the final results. As can be seen, from the detailed calculation process of these three companies, the X_5 (ORTA) contributes most to the final Z' values. On the other hand, since the Z'' value is not affected by X_5 (ORTA), the results are dominated by X_1 (WCTA) and X_3 (EBITTA).

In the case of Germania (see Table 4), it already showed negative retained earnings, negative EBIT, and negative equity 4 years before the bankruptcy. Z'-score did not detect the serious situation because Germania still had good sales at that time, and the X_5 (ORTA) variable contributed significantly to the Z' value results. On the contrary, Z'' successfully detected the financially distressed situation of Germania as it showed Z'' values in the danger zone 4 years prior to bankruptcy. Aigle Azur has totally distinctive Z' and Z'' classification results (see Table 5): Z''-scores in the danger zone for nine consecutive years before bankruptcy while Z'-score only within the gray zone. Moreover, when focusing on the 4 years before failure (2013–2016), it showed negative Z'' values that indicated a severe situation, while its Z' values maintained the average level. This is because, although X_1

TABLE 3 Z'- and Z''-score classification results of bankrupted sample airlines.

Z'-score classification results				Z''-score classification results			
Predicted		Unpredicted		Predicted		Unpredicted	
1	Air Berlin	1	Thomas Cook	1	Air Berlin	1	Thomas Cook
2	Transero	2	Niki	2	Transero	2	Niki
3	Spanair	3	Vim Airlines	3	Spanair	3	Vim Airlines
4	Monarch	4	Germania	4	Monarch		
5	Aerosvit	5	Flybmi	5	Aerosvit		
6	Clickair	6	Aigle Azur	6	Aigle Azur		
7	Air Comet			7	Germania		
8	Openskies			8	Clickair		
9	Islas Airways			9	Air Comet		
10	Quantum			10	Flybmi		
11	Helitt			11	Openskies		
				12	Islas Airways		
				13	Quantum		
				14	Helitt		

Source: Amadeus and SABI database, elaborated by authors.

TABLE 4 Disaggregation of calculation process of Z' and Z'' values of Germania.

$Z' = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0.998\ X_5$						
Germania	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	ORTA (X_5)	Z' value
2008	0.417	0.208	0.437	0.137	2.916	4.115
2009	0.459	0.336	0.694	0.277	3.216	4.983
2010	0.349	0.446	0.148	0.469	4.667	6.079
2011	0.505	0.481	0.103	0.554	5.740	7.383
2012	0.427	0.460	0.050	0.501	4.905	6.344
2013	0.223	0.260	0.054	0.186	6.583	7.305
2014	0.043	−0.144	−0.423	−0.061	7.813	7.228
2015	0.233	−0.217	−0.275	−0.027	5.362	5.076
2016	0.143	−0.323	−0.230	−0.064	5.109	4.635
2017	0.010	0.193	0.042	0.165	1.743	2.153
$Z'' = 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4$						
Germania	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	-	Z'' value
2008	3.816	0.800	0.945	0.342	-	5.903
2009	4.200	1.294	1.502	0.692	-	7.688
2010	3.192	1.719	0.319	1.173	-	6.403
2011	4.624	1.852	0.222	1.384	-	8.082
2012	3.907	1.772	0.108	1.253	-	7.039
2013	2.040	1.000	0.116	0.466	-	3.621
2014	0.389	−0.555	−0.915	−0.152	-	−1.233
2015	2.132	−0.833	−0.595	−0.068	-	0.636
2016	1.305	−1.243	−0.497	−0.160	-	−0.595
2017	0.088	0.743	0.092	0.412	-	1.336

Note: X_1 = Working Capital/Total Assets (WCTA); X_2 = Retained Earnings/Total Assets (RETA); X_3 = EBIT/Total Assets (EBITTA); X_4 = Book Value of Equity/Total Liabilities (BVETD); X_5 = Operating revenues/Total Assets (ORTA).
Source: Amadeus and SABI database, elaborated by authors.

(WCTA), X_2 (RETA), and X_4 (EBITTA) are negative, once one includes X_5 (ORTA), the results of Z'-score turned positive. Flybmi is similar to Aigle Azur (see Table 6), in that X_5 (ORTA) causes different classification results of Z' and Z''. While the Z' values are mostly in gray zone, the Z''-score, without the influences of sales, showed negative values which reveal the financial distress of the firm prior to bankruptcy.

Regarding question (b), we studied the three cases of bankruptcy and found that two of these three companies failed due to factors other than financial. Thomas Cook Airline Limited ceased operations because its owner company, Thomas Cook Group plc, went into compulsory liquidation along with all UK entities (BBC news, 2019), including Thomas Cook Airline Limited. VIM Airlines suspended operations because its CEOs were arrested for embezzlement, and then the airline's license was invalidated by the Russian authorities. Niki was the only airline that had been in operating troubles and had not been detected as in financial distress before failure. It is a particular case because during the last few before failure, it merged with Air Berlin (in late 2011). Although it maintained the operating revenues, it showed a significant decrease (more than half of the total amount) in EBIT from 2012. Afterward, it canceled several flight routes and changed aircraft, and its total assets were significantly reduced from 312 million euros in 2011 to 79 million euros in 2016. Looking into the calculations of Z'-score and Z''-score, variables X_1 (WCTA), X_2 (RETA), X_3 (EBITTA), and X_5 (ORTA) are all related with total assets. In this case, although the numerators as working capital, retained earnings, EBIT, and operating revenues are stable, due to the sharp decrease in total assets as denominator, the Z-scores show an increasing pattern.

After evaluating the predictive power of Altman Z'-score (1983) and Z''-score (2017) models, we are encouraged by the good performance of Z''-score applied in the service sector as air transportation. Therefore, in the last part of this section, we carried out the Z''-score application analysis on 17 active European airlines aiming to evaluate their financial distress likelihood. The Z''-score calculation results as well as the classification results are presented in Figure 5 and Table 7.

The results in Figure 5 indicate that the majority of sampled active airlines have had Z'' value in distress zone during the last 10 years, which suggests financial distress risk. Some big flag carriers as Lufthansa and Air France-KLM show constant low Z'' values. Lufthansa's 10 years Z'' values barely reached 1, and Air

TABLE 5 Disaggregation of calculation process of Z' and Z'' values of Aigle Azur.

$Z' = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0.998\ X_5$						
Aigle Azur	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	ORTA (X_5)	Z' value
2007	0.10	0.07	0.04	0.07	2.85	3.12
2008	0.01	0.03	−0.08	0.04	2.84	2.84
2009	0.01	0.02	0.06	0.04	2.62	2.75
2010	−0.01	0.07	0.27	0.06	2.26	2.65
2011	−0.03	0.06	0.04	0.05	2.17	2.30
2012	−0.01	0.07	0.11	0.06	2.27	2.50
2013	−0.07	0.01	−0.21	0.02	2.56	2.31
2014	−0.15	−0.07	−0.20	0.00	2.90	2.48
2015	−0.10	−0.14	−0.04	−0.03	2.70	2.39
2016	−0.16	−0.19	−0.07	−0.04	2.73	2.27
$Z'' = 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4$						
Aigle Azur	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	-	Z'' value
2007	0.91	0.25	0.08	0.18	-	1.42
2008	0.11	0.10	−0.18	0.11	-	0.14
2009	0.11	0.09	0.13	0.09	-	0.42
2010	−0.11	0.27	0.58	0.16	-	0.89
2011	−0.25	0.23	0.09	0.14	-	0.20
2012	−0.12	0.27	0.24	0.15	-	0.54
2013	−0.62	0.02	−0.46	0.06	-	−1.00
2014	−1.34	−0.29	−0.43	0.01	-	−2.05
2015	−0.90	−0.54	−0.09	−0.07	-	−1.61
2016	−1.48	−0.72	−0.14	−0.11	-	−2.45

Note: X_1 = Working Capital/Total Assets (WCTA); X_2 = Retained Earnings/Total Assets (RETA); X_3 = EBIT/Total Assets (EBITTA); X_4 = Book Value of Equity/Total Liabilities (BVETD); X_5 = Operating revenues/Total Assets (ORTA).
Source: Amadeus and SABI database, elaborated by authors.

TABLE 6 Disaggregation of calculation process of Z' and Z'' values of Flybmi.

$Z' = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0.998\ X_5$						
Flybmi	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	ORTA (X_5)	Z' value
2013	−0.24	−0.17	−0.56	−0.07	2.60	1.57
2014	−0.11	−0.11	−1.61	0.02	2.93	1.12
2015	−0.31	−0.32	−1.17	−0.04	3.44	1.61
2016	−0.15	−0.35	−0.21	0.06	2.72	2.07
2017	−0.09	−0.39	−0.49	0.08	2.49	1.60
$Z'' = 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4$						
Flybmi	WCTA (X_1)	RETA (X_2)	EBITTA (X_3)	BVETD (X_4)	-	Z'' value
2013	−2.19	−0.64	−1.20	−0.17	-	−4.21
2014	−1.01	−0.42	−3.49	0.06	-	−4.86
2015	−2.84	−1.21	−2.53	−0.11	-	−6.68
2016	−1.37	−1.35	−0.46	0.16	-	−3.02
2017	−0.86	−1.50	−1.05	0.20	-	−3.21

Note: X_1 = Working Capital/Total Assets (WCTA); X_2 = Retained Earnings/Total Assets (RETA); X_3 = EBIT/Total Assets (EBITTA); X_4 = Book Value of Equity/Total Liabilities (BVETD); X_5 = Operating revenues/Total Assets (ORTA).
Source: Amadeus and SABI database, elaborated by authors.

MODEL/COMPANY	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Lufthansa	1.009	0.863	0.779	-0.403	0.255	0.636	1.154	0.639	0.688	1.257
Air France-KLM	-3.555	-0.693	-1.467	-1.509	-1.303	-0.777	-0.063	-1.104	-1.096	-2.868
Turkish Airlines (emer)	4.490	4.558	4.127	4.225	4.466	3.995	4.554	4.697	4.342	3.468
Easyjet	-1.471	-1.630	-0.753	-1.126	-0.404	-0.294	-0.694	-0.307	-1.101	-3.648
British Airways	0.836	0.153	0.321	0.185	0.922	1.210	2.000	1.926	1.315	-2.763
Aeroflot (emer)	8.136	7.380	8.246	6.263	4.691	6.824	6.765	3.503	3.857	1.672
TUI Airways	1.583	4.612	7.514	8.311	7.086	3.342	3.565	5.316	3.296	-0.530
Virgin Atlantic	-0.138	-1.166	-0.942	-1.316	-0.839	0.332	-1.116	-1.140	-0.094	-1.550
Finnair	1.011	1.636	1.123	1.000	2.815	2.960	2.887	2.564	1.722	1.455
Norwegian Air Shuttle	-0.195	-0.227	0.421	-1.671	-0.815	-0.640	-1.287	-2.351	-0.706	-1.390
Air Europa	0.670	0.388	2.262	1.544	0.747	0.766	0.437	1.141	0.727	-8.737
Rossiya Airlines (emer)	-1.266	1.002	-0.425	-0.208	1.210	3.290	3.740	3.552	2.957	-0.143
Polskie LOT (emer)	1.957	0.251	1.697	2.436	2.185	3.264	3.561	3.424	3.302	3.475
Brussels Airlines	0.045	0.622	1.049	1.568	2.622	2.322	1.222	1.222	-0.127	-9.320
Aer Lingus	1.234	-0.939	-0.922	-2.478	-0.486	2.117	2.256	1.463	0.095	-3.208
TUI airlines Belgium	2.924	2.427	3.648	2.655	2.623	2.846	3.093	2.786	0.890	-6.392
Nordwind Airlines (emer)	4.898	2.283	2.774	3.383	2.080	0.773	2.689	4.086	3.593	-3.021

FIGURE 5 Z''-score results of active sampled companies. *Source*: Amadeus database, elaborated by authors.

TABLE 7 Z''-score classification results of active sample airlines.

	1 year in distress	2 years in distress	4 years + in distress
1	British Airways	Air Europa	Air France-KLM
2	TUI Airways	Brussels Airlines	Easyjet
3	Rossiya Airlines	Aer Lingus	Virgin Atlantic
4	Nordwind Airlines	TUI Airlines Belgium	Norwegian Air Shuttle

Source: Amadeus database, elaborated by authors.

France-KLM shows all negative Z'' values. Other low-cost carriers such as Easyjet and Norwegian Air Shuttle, and Virgin Atlantic also show almost 10-year negative Z'' values. This finding is consistent with Stepanyan (2014) that most leading US airlines show Z values in distress zone during 2007–2012.

The impact of the COVID-19 pandemic has been reflected in the Z'' values of sampled airlines. It can be observed that, for example, Air Europa, Brussel Airlines, and TUI Airlines Belgium experienced a dramatic drop of Z'' values. TUI Airways, Rossiya Airlines, and Nordwind Airlines had Z'' values in safe zone in 2019 and negative Z'' values in distress zone in 2020.

Five airlines from emerging markets all show safe zone for more than 6 years. It may be due to the constant coefficient of 3.25 for emerging market which contributes significantly to the Z'' results.

We can observe from Table 7 that only five of the 17 sampled active airlines are in safe zone or gray zone, while 12 of them show Z'' values in distress zone during the last one, two, or more than 4 years. Airlines that have 4-year consecutive Z'' values in distress zone could be considered as bearing high risk of financial distress (Stepanyan, 2014). It should be mentioned that in 2020, both Norwegian Air Shuttle and Virgin Atlantic filed for bankruptcy protection. From the results obtained, we consider that it is important for airlines such as Air France-KLM and Easyjet to build an early-warning procedure for detecting and monitoring the potential financial distress risk so as to act proactively in the crisis of COVID-19. Also, it is worth mentioning that Air France-KLM as flagship carrier has received a great amount of financial aid from the Netherlands and France. Governments' bailout may relieve its financial distress situation. This may explain why Air France-KLM can maintain operations with negative Z'' values in the last 10 years. However, Easyjet, as a non-flagship carrier, received less government support and no tailored bailout package. It implies a less clear future position of Easyjet in the post-COVID-19 era (Albers & Rundshagen, 2020).

6 | CONCLUSION

We carried out an empirical study to assess the predictive capability of the Altman Z'-score (1983) and Z''-score (2017) models on European airlines that went bankrupt during 2009–2020. This paper contributes to the existing literature as an application study of bankruptcy prediction model on European airline data. In the descriptive analysis of our sample, we first analyzed changes in Working capital, EBIT, and D/A ratios. We found that the majority show a low level of Working capital and EBIT (zero or negative) before failure (from 3 to 10 years, depending on the data availability). Regarding D/A ratio trends, almost all bankrupt airlines had D/A ratios near 100% and some reached 200% and even higher.

The results reveal that first, airline companies often show lower Z values compared with other sectors, which aligns with the findings of several previous studies (Chung & Szenberg, 2012; Gritta et al., 2011; Kolte et al., 2018; Stepanyan, 2014). The findings of this study, along with previous literature, indicate that European airlines and the US airlines both tend to show low Z values that are classified in distress zone according to the interval constructed by Altman. Second, the Z'-score as a model for private manufacturing companies shows a lower predictive capacity than the Z''-score for airline companies. It is reasonable that the Z''-score has a better performance as it is declared suitable for public and private manufacturing and non-manufacturing firms. In this case, we analyzed air transportation which is a service-type industry and the Z''-score model shows a more sensitive and accurate performance. Third, as accounting information-based models, Z' and Z'' values may be not capable of detecting business bankruptcies that are caused not primarily by financial factors, but for other reasons such as board of management and administration issues. Based on the results obtained in the active airlines' analysis, we consider that Z''-score model is a promising method to predict the financial distress of airlines due to COVID-19.

The implication of this study is not only theoretical but also practical. The findings of our study pave the way for an early-warning method for European airline bankruptcy. It conducted a theoretical test of the effectiveness of important ratios for financial health evaluation and failure prediction of likely for airline companies in particular. Although Z'-score and Z''-score models have been applied in the literature for US airlines, the same is not true for European airlines. In 2019, the European Parliament and the Council published a new Restructuring Directive on preventive restructuring frameworks. As debtor-in-possession-type insolvency regimes like Chapter 11 in the United States and scheme of arrangement in the United Kingdom, the EU Restructuring Directive helps debtors in financial difficulty and stimulates the effectiveness of restructuring procedures. It is considered that comparing with the Chapter 11 in the United States, the Directive's framework is arguably more streamlined and more cost-effective due to a minimized judicial intervention (Lerner & Belovičová, 2019). However, comparing the European Restructuring Directive and the US Chapter 11, some differences can be addressed. First, the European Relative Priority Rule is less rigid than the US Absolute Priority Rule. It is revealed that in the European style, "dissenting voting classes are to be treated at least as favourably as any other class of the same rank and more favourably than any junior class". Second, senior creditor's exit right is more protected in the case of the European system. However, a weakness is suggested by some authors (Lerner & Belovičová, 2019) regarding the European Directive since debtors are not offered as a super-priority. Our results broaden the existing literature by providing useful insights for scholars and researchers who are interested in assessing the financial distress situation of the European aviation industry.

Practically, boards of directors can use the Altman Z' (1983) and Z''-score (2017) models to assess the financial health and take proactive actions to prevent possible failure by improving productivity and balancing capital deployment so as to implement corrective measures and adjust financial structure. Investors can also apply this model to evaluate the performance of a target airline company and identify its financial status to avoid likely future losses. Also, policymakers could use these models to supervise the financial health of airlines and pay closer attention to the potential bankruptcy candidates. At the national and international levels, it could help authorities take precautionary measures to soften the negative effects that airline bankruptcies may bring to passengers, suppliers, employees, and other stakeholders. Under the circumstance of the pandemic COVID-19, European authorities implemented distinctive support measures to help airlines and to avoid potential bankruptcy. Some countries offered financial support only to their flagship carriers or native carriers, while other airlines claim it as a discriminatory act since a huge amount of state aid are gifted to flag carriers (O'Leary, 2020). Such a measure is seen as having a potential negative impact on the competitiveness and effectiveness of the European airline market. Chapter 11 is suggested to be effective at reducing fixed costs of airline industry (Ciliberto & Schenone, 2012). However, considering some criticism of Chapter 11, it may be seen as an indirect subsidy to the US airlines and allow inefficient firms to reorganize (Bock et al., 2019). More specifically, it is argued that Chapter 11 could give weak companies unfair advantages and damage the market competition environment (Gong, 2007). Policymakers should also be concerned about this issue in the European Restructuring Directive framework as well as the unequal state aid provided to airlines that may set back the European air transport market. Comparing with the United States, EU member states show less consensus which implies less legal harmonization in insolvency law. Such inconsistency should also be concerned for ensuring a long-term market competition.

Overall, the results of our analysis are promising and suggest the viability of Z''-score model (2017). As a multi-country bankruptcy prediction model, it can provide useful information to predict the future financial distress of European airlines due to COVID-19.

7 | LIMITATION AND FUTURE RESEARCH

One of the major limitations is that although we believe that updated Z-score models have great potential, they only take a financial accounting perspective. However, the situation of financial distress or bankruptcy in airline industry can be influenced by various factors. Although other factors may also appear in the accounting data of airlines, they cannot be immediately transmitted to the financial statement. The second limitation is that of data availability, as the majority of European airlines are private firms and sampling is limited that data of 2021 are not available yet. Other databases may help in this regard.

Future research may focus on the accuracy analysis of prediction models such as the ROC (return on capital) ratio and AUC (area under curve) in order to determine which of the analyzed models have the better classification performance. Another possibility is to compare the Z-score with other standard metrics (e.g., P-score and Airscore) in terms of bankruptcy prediction capacity, especially in the situation of pandemic context. Future researchers are encouraged to investigate alternative models to predict the current crisis the airline industry is facing due to COVID-19.

AUTHOR CONTRIBUTIONS

We declare that all authors contributed equally to the paper.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

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