UNIVERSITAT ROVIRA I VIRGILI

BANKRUPTCY PREDICTION ANALYSIS: APPLICATION OF ALTMAN Z-SCORE APPROACH IN AIRLINE INDUSTRY

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BANKRUPTCY PREDICTION ANALYSIS: APPLICATION OF ALTMAN Z-SCORE APPROACH IN AIRLINE INDUSTRY

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INTRODUCTION

Bankruptcy prediction has been a subject of research since 1932 when Fitzpatrick published a study comparing failed and successful firms. Since 1968 when Altman introduced the breakthrough bankruptcy prediction model—Altman Z-score, a large body of research started to focus on the prediction of corporate financial distress. Air transport was one of the fastest-growing industries, offering more than 80 million jobs across the world and contributing 8% to gross domestic product. The European airline industry is highly fragmented because most members of the European Union consider it is important to have a national air carrier. However, over half of the profit of the whole industry is shared by four big airlines which lefts other airlines in a difficult situation. There is a series of bankruptcy events in the European aviation industry, even for big airlines and flag carriers such as Air Berlin and Alitalia. It is crucial to determine financial distress risk for airlines since it can provide early-warning messages on aspects that can be seen and addressed by executives and managers.

The COVID-19 pandemic caused immense disruption to the global economy and resulted in a dramatic decrease in demand for air travel, which left global air carriers struggling for survival in the worst situation they have ever encountered. In recent years, the concept of corporate sustainability has an increasing impact in the field of the business world. Scholars sought to investigate whether Corporate Sustainability practice could reduce the financial distress risk of companies. Asian-pacific region gathered more than half of the world's population while Asian-pacific airlines show poor CSR performance compared with airlines in Western countries. This is assumed that because the concept of CSR is initially proposed in Western countries and the Asia-pacific countries are just starting to adopt the practice.

This thesis contributes to the literature of financial distress prediction using Altman Z-score on the airline industry, and it took the further step of investigating the moderating role of European flag carriers in the relationship between key financial ratios and financial distress risk, as well as the moderating role of Asian-pacific airlines in the relationship between ESG practices and financial distress risk. This thesis is consisted of five studies organized as independent chapters, and has been structured as follows:

Chapter 1 provided a systematic literature review of corporate bankruptcy prediction. It aimed at obtaining a comprehensive overview of existing literature, as well as the co-authorship and primary methods that have been studied regarding the research topic of the present thesis. We found firstly that the research topic of bankruptcy prediction was a field of growing interest, supported by the fact that the number of related publications has been boosted especially after the 2008 global crisis. Secondly, a weak co-authorship has been detected, implying that limited collaboration existed among researchers in this field. Finally, we found that the most frequently used models in this area were Logistic regression and Neural networks, while there was an emerging trend of using computer science and artificial intelligence, which arouse the research interest of analyzing the innovative method of bankruptcy prediction.

Chapter 2 took a further step based on the results obtained in Chapter 1. The existing literature showed that there was an emerging tendency of using the innovative approach with help of computer science and artificial intelligence techniques. Therefore, we conducted a bibliometric study on intelligent techniques of bankruptcy prediction. We sought to identify the bibliometric trends with aspects such as geographical area of authors, co-citation, and co-occurrence, and we also obtained under-explored areas as opportunities for future research.

In Chapter 3, we provided a unique and novel perspective on the predictive power of the Altman Z-score in the European aviation industry. By applying the Altman Z'-score for private firms and Altman Z''-score for private and non-manufacturing firms on 17 European airlines that bankrupted from 2009 to 2019, we first found airlines show lower Z value compared with other sectors. Secondly, we noticed that Z''-score performs better than Z'-score when predicting bankruptcy of European airlines. Thirdly, Z-score as an accounting information-based model had limited prediction power in cases that bankruptcy was not mainly caused by financial factors but reasons like management board and administration problems.

Chapter 4 analyzed the determinants of financial distress in the European aviation industry with a special focus on the impact of the flagship. Under a turbulent situation like the COVID-19 pandemic, flag carriers tend to benefit from a special advantage from national support. Meanwhile, flag carriers are often considered being inefficient and with low performance. We examined the moderating role of being a flag-carrier in the relationship between leverage, liquidity, profitability, and the degree of financial distress by a panel data analysis. The results indicated that the negative impact of leverage was higher in the case of flag carriers while the positive influences of profitability and liquidity were also higher for flag carriers than non-flagship carriers. Since firms with high profitability will have a higher capacity to use debt and need more benefits from tax deductions, it is essential for flag carriers to assess the degree of leverage for controlling the financial distress risk.

Chapter 5 aggregated the concept of sustainability. It is suggested by previous studies that in a turbulent period, companies with higher ESG (environmental, social, and governance) engagement suffered lower downside risk. Based on this, we sought to examine the relationship between ESG pillar score and the likelihood of financial distress. Since the Asia-pacific region gathered more than half of the world's population and Asia-pacific airlines obtained a higher profit margin compared with airlines from other regions, the sustainability issue for freight activities in this region was gaining more concern. We investigated the moderating role of being an Asia-pacific airline in the relationship between ESG and financial distress risk. The findings suggested an insignificant relationship between environmental and social pillar scores and financial risk. Governance did have a positive impact on reducing the financial distress risk of airlines, and such positive impact was greater in the case of Asia-pacific airlines.

Finally, the overall conclusion was presented, including all key findings, insights and clarifying the contribution to the existing literature.

Chapter 1

1. AN OVERVIEW OF BANKRUPTCY PREDICTION MODELS FOR CORPORATE FIRMS: A SYSTEMATIC LITERATURE REVIEW

Overview: The aim of this paper is to conduct a literature review of corporate bankruptcy prediction models, on the basis of the existing international academic literature in the corresponding area. It primarily attempts to provide a comprehensive overview of literature related to corporate bankruptcy prediction, to investigate and address the link between the different authors (co-authorship), and to address the primary models and methods that are used and studied by authors of this area in the past five decades. The results verified, firstly, that bankruptcy prediction in the corporate world is a field of growing interest, as the number of papers has increased significantly, especially after 2008 global financial crisis, which demonstrates the importance of this topic for corporate firms. Secondly, it should be mentioned that there is little co-authorship in this researching area, as researchers with great influence were barely working together during the last five decades. Thirdly, it has been identified that the two most frequently used and studied models in bankruptcy prediction area are Logistic Regression (Logit) and Neural Network. However, there are many other innovative methods as machine learning models applied in this field lately due to the emerging technology of computer science and artificial intelligence.

Keywords: bankruptcy prediction, business failure, financial distress, insolvency, default firm, SLR
JEL codes: G10, G33, M21

1.1. Introduction

Over the past 50 years, bankruptcy prediction has been a field of increasing interest to researchers all around the world. Many academic studies have been dedicated to exploring a corporate failure prediction model with the best accuracy. Since the breakthrough bankruptcy prediction model was introduced by Altman in 1968, a large body of research focuses on the prediction of corporate financial distress. In most cases, authors tend to use the ultimate failure (bankruptcy) as the dividing line when they distinguish the failed and non-failed firms.

The exact definition of financial distress is not determined yet. From the perspective of theoretical analysis, financial distress has different degrees (Bruynseels and Willekens 2012). Mild financial distress may be reflected as temporary cash flow difficulty, such as the concepts like insolvency, default and etc. The most serious one is called the business failure, or bankruptcy (Sun et al. 2014). Business failure leads to the discontinuity of the firm's operation, and it has a significant effect on anyone who is related to the firm (creditors, stockholders, suppliers, etc.). Consequently, the establishment of reliable business failure prediction models is of importance to the current corporate firms (Zopounidis and Doumpos 1999).

This study has been conducted based on research primarily using the database Scopus, considering the timeframe from 1968 (the year when Altman published the Z-score model) to 2017. Twelve keywords (six primary and six secondary) were used to carry out the present literature review: Bankruptcy, Failure, Default, Distress, Early-warning, Insolvency, Score, Indicator, Ratio, Model, Prediction and Forecast. The outcome was a total of 36 combinations of keywords being used in this study so as to search the literature for framing the concept of bankruptcy prediction.

The main purpose of this study is to obtain a broader idea of the bankruptcy prediction concept, through identifying, critically evaluating and integrating findings of all relevant and high-quality studies using Scopus database. Furthermore, the trend of the development of bankruptcy prediction studies and the co-authorship among the main researchers in this area should be shown as well.

Other additional objectives are as follows:

— To observe the evolution of papers published during the years 1968-2017. (It should be noted that the year 2017 in this paper refers to a review done up to 31 December 2017)

— To identify the most frequently cited papers

— To identify the main journals in relation to the studied research field.

— To show the co-authorship among the the main researchers in this area.

— To identify the most frequently used and studied models and methods in this area.

Therefore, this study is structured as follows: the first section introduces and explains the field of interest: corporate bankruptcy prediction; the second section presents the literature review of bankruptcy prediction. Section three describes the methodology applied for the study and section four provides an overview on the existing international literature in this research field. The fifth section displays the results and findings of the study. The final section presents conclusions drawn from this research.

1.2. The literature review of bankruptcy prediction

1.2.1. Different terms to describe business failure

In the literature, various authors define differently the failuree of business in their studies.
Dimitras et al. (1996) indicates that in the past and current investigations in business failure prediction area, scholars usually do their researches by studying some particular aspects or stages of business failure process depending on their own experience or interests, without or with little reference to the theoretical framework. It causes that the literature of business failure is highly fragmented, as well as the ambiguity of the definition of business failure.

According to Balcaen (2006), the criterion of failure is chosen arbitrarily in historical studies, whether a juridical definition of failure, namely bankruptcy (Altman et al. 1994; Hillegeist et al. 2004; Wilson and Sharda 1994; Fletcher and Goss 1993; Lee et al. 1996), or a financial distress definition is used (Pan 2012; Jones and Hensher 2004; Sun and Li 2008; Xiao et al. 2012). The latter can also be described as failure-related events such as insolvency (Langford et al. 1993; Lepetit and Strobel 2013, Jackson and Wood 2013), default (Tserng et al. 2014; Peresetsky et al. 2011), and etc. Meanwhile, Altman and Hotchikiss (2006) also comment that there are basically four genetic terms to describe those unsuccessful business enterprises which are failure, insolvency, default and bankruptcy.

According to the economic criteria, failure is interpreted by Altman and Hotchikiss (2006) as the realized rate of return on invested capital which is dramatically and continually lower than prevailing rates on equivalent investments taking risk into consideration.

Insolvency takes place when the liabilities of a firm are greater than its assets. It makes a firm be incapable to meet its current obligations, sending a signal of a lack of liquidity (Altman and Hotchikiss 2006).

Default, literally occurs when a firm fails to fulfil an obligation, especially to pay a loan or appear in a low court. Using more corporate terms, default happens when the debtor violates a condition of an agreement with a creditor and can be the grounds for legal action. (Altman and Hotchikiss 2006)

Altman and Hotchikiss (2006) state that there are two types of bankruptcy. The first refers to the net worth position of an enterprise. The second type which is more observable refers to the firm's formal declaration in a federal district court, accompanied by a petition either to liquidate its assets or attempt a recovery program. While Ross et al. (1999) concluded by summarizing the previous studies that there are three types of bankruptcy: legal bankruptcy, which literally means that the company goes to court for a declaration of bankruptcy; technical bankruptcy, which describes the situation that a company cannot fulfill the contract on schedule to repay principal and interest; and accounting-bankruptcy, which refers to the situation when a company is simply showing negative book net assets.

Other authors investigate early warning signals which provides forecasting of bankruptcy risk of firms (Korol and Korodi 2011). The word early warning was used originally in the military area, but now this concept is widely applied in some other fields such as: macroeconomics, business administration, environmental monitoring, and etc. Therefore, early warning of business failure is also an important term in the research field of bankruptcy prediction.

1.2.2. Models applied by different authors

Since Altman published one of the most well-known bankruptcy prediction models in 1968, a multitude of bankruptcy prediction models have flooded the literature (Gissel et al. 2007). It not only means the increasing number of papers published, but also the variety of the models used for business failure prediction. Thanks to the development of statistical techniques and information technology in recent years, more and more different predictive methods have been applied in order to establish a bankruptcy prediction model with a better accuracy.

Altman's model in 1968 is a five-factor multivariate discriminant analysis model. According to Gissel et al. (2007), the primary methods that have been used for model development are multivariate discriminant analysis (MDA), logit analysis, probit analysis, and neural networks. Especially from the 1990's, due to the fact that scholars are becoming more interested in artificial intelligence technology, neural network has become one of the most widely used promising tools. Applying this method, studies carried out by Tam and Kiang (1992), Altman et al. (1994), Wilson and Sharda (1994), Fletcher and Goss (1993), Lee et al. (1996) have had great influence on later research related to business failure prediction. Furthermore, Pan (2012) intended to optimise General Regression Neural Network model applying algorithm and obtained a good convergence result which indicates the good prediction capability of the model.

At the same time, there are also other methods based on machine learning and artificial intelligence adopted by many authors in bankruptcy prediction area, such as rough set (Beynon and Peel 2001; Mckee 2003; Xiao et al. 2012; Wang and Wu 2017), case-based reasoning (Li and Sun 2009; Li and Sun 2011), support vector machine (Lin et al 2011; Li and Sun 2012; Kim 2011; Chandra et al. 2010) and so on. Rough set theory has been applied to a wide variety of financial decision analysis problems and it was created originally for dealing with the problem of apparent indiscernibility between objects in a set. It has had a reported bankruptcy accuracy ranging from 76% to 88%. Case-based reasoning, as an effective and easily understandable method for solving real-world problems, has become a vital methodology in the current business failure prediction area due to its simplicity, competitive performance with modern methods, and ease of pattern maintenance (Li et al. 2011) Support vector machine, arose from the area of statistical learning theory and was applied into business failure prediction for the first time in 2005

(Shin et al. 2005; Min and Lee 2005), and proved to be superior to the performance of artificial neural network. (Kim 2011)

Since there is an increasing number of papers published related to business failure prediction from year 2000 and some other authors shed light on carrying out overviews or comparison of the business failure prediction models. Hillegeist et al. (2004) compare two accounting-based models, Altman’s (1968) Z-score and Ohlson’s (1980) O-score, with a market-based model developed by themselves based on Black-Scholes-Merton option-pricing model, showing that the latter can provide significantly more information than the former two. Balcaen et al. (2006) undertake an overview of classic statistical methodologies in the recent 35 years, in order to understand their features as well as their related problems.

1.3. Methodology

Firstly, a systematic literature review (SLR) has been carried out applying bibliographic database Scopus, in order to identify the core papers which were published in English during the period of 1968-2017. The principal purpose is to “find all relevant individual studies, thereby making the available evidence more accessible to decision-makers.” (CRD 2009)

The SLR methodology is an essential feature of any academic project. It helps the researchers to get more information about their research topic (Webster and Watson 2002) as it aims to address the problem by identifying, critically evaluating and integrating the findings of all relevant, high-quality, individual studies. The advantages of the SLR can be concluded as its providing of reliable information since it improves methodological transparency and enables future replication. With respect to the database applied, Scopus offers a wide overview of researches of the world, providing a massive abstract and citation database of scientific journals, books and conference proceedings (Elsevier 2015)

Secondly, with the purpose of analyzing co-authorship among different articles related to bankruptcy prediction, the program NodeXL was used to facilitate the identification of the concepts and to create a network analysis that is visualized in a way so as to make it easy to observe the existing relationships among different authors (NodeXL 2013).

1.4. Identification of keywords and article sampling.

In order to answer the research questions, initial search for identifying the international academic papers related to the research topic were carried out by using 36 combinations of a total of twelve keywords (six primary and six secondary) as searching criteria. The details of the keyword combination design as shown below in figure 1.1:

Figure 1.1: Design of keywords combinations for the initial searching

Bankruptcy **OR** Default Firm **OR** Early-warning **OR** Failure Prediction **OR** Financial Distress **OR** Insolvency	**AND**	Model **OR** Prediction **OR** Forecast **OR** Indicator **OR** Ratio **OR** Score

After applying all considered combinations of primary and secondary keywords, the total number of the publications that had been found in Scopus database (up to December 2017) was 1259. The detailed search results are divided into six sections as shown in the tables 1.1 to 1.6:

Table 1.1: Searching result using combination of keywords set number 1

Secondary keyword	Primary keywords	Number of articles
Model	Bankruptcy	169
	Default firm	10
	Early-warning	123
	Failure prediction	77
	Financial distress	85
	Insolvency	28
Total		492

Table 1.2: Searching result using combination of keywords set number 2

Secondary keyword	Primary keywords	Number of articles
Prediction	Bankruptcy	184
	Default firm	5
	Early-warning	36
	Failure prediction	186
	Financial distress	63
	Insolvency	16
Total		490

Table 1.3: Searching result using combination of keywords set number 3

Secondary keyword	Primary keywords	Number of articles
Forecast	Bankruptcy	7
	Default firm	0
	Early-warning	3
	Failure prediction	16
	Financial distress	4
	Insolvency	2
Total		32

Table 1.4: Searching result using combination of keywords set number 4

Secondary keyword	Primary keywords	Number of articles
Indicator	Bankruptcy	7
	Default firm	0
	Early-warning	59
	Failure prediction	2
	Financial distress	7
	Insolvency	2
Total		77

Table 1.5: Searching result using combination of keywords set number 5

Secondary keyword	Primary keywords	Number of articles
Ratio	Bankruptcy	54
	Default firm	1
	Early-warning	2
	Failure prediction	21
	Financial distress	28
	Insolvency	9
Total		115

Table 1.6: Searching result using combination of keywords set number 6

Secondary keyword	Primary keywords	Number of articles
Score	Bankruptcy	28
	Default firm	2
	Early-warning	1
	Failure prediction	5
	Financial distress	9
	Insolvency	8
Total		53

Among all the results searched by using every combination of keyword, there is one primary keyword "Bankruptcy" presents highest amount of publications when it is combined with the secondary keywords (See Table 1.7).

Table 1.7: Searching result using combination of keywords set number 7

Primary keyword	Secondary keywords	Number of articles
Bankruptcy	Model	169
	Prediction	184
	Forecast	7
	Indicator	7
	Ratio	54
	Score	28
Total		449
Proportion of total searching results		35.7%

The sampling and selection process of papers has been carried out considering the following steps, as seen in Table 1.8. Firstly, duplicates were removed in order to ensure unbiased results. Secondly, the exclusion of articles was realized on the basis of reviewing the title and abstract. Studies that are related to corporate bankruptcy prediction and were published within the period between 1968 and 2017 were included in our review. Also, those studies focusing on subjects other than corporate bankruptcy predications were excluded as it would not necessarily be highly corresponded to the research topic. For instance, papers related to the prediction of weather or early-warning of the potential wildfire in the forest were not included into this review. After examining the abstracts of the rest 676 papers, those studying prediction models designed for macroeconomic aspect which are not precisely of the corporate area, were also removed. Finally, 496 papers have been included as literature for the present review.

Table 1.8: Sample of publications SCOPUS

Concept	Eliminated	Number of considered paper for the SLR
Total initial search results	-	1,259
Removal of duplicates	515	744
Removal of "non-applicable" papers by each combination (title)	(68)	676
Removal of "non-applicable" papers by each combination (abstract)	(179)	496

Additionally, due to the fact that the most classic study in this research topic, published by Altman in 1968 -Financial Ratios, Discriminant Analysis And The Prediction Of Corporate Bankruptcy- is not included in the list of searching results, while the used searching keywords are highly coincided with the keywords established by the author Altman, we consider the technologic limitation of that period may cause a non-digital keywords identification, which unable the automatic link between the used searching keyword and the article. Therefore, considering the importance of this article, the authors decide to add it manually into the literature.

According to the procedure followed, the final set of relevant articles consisted of 496 academic articles, which were used as the basis for the present study.

1.5. Descriptive results

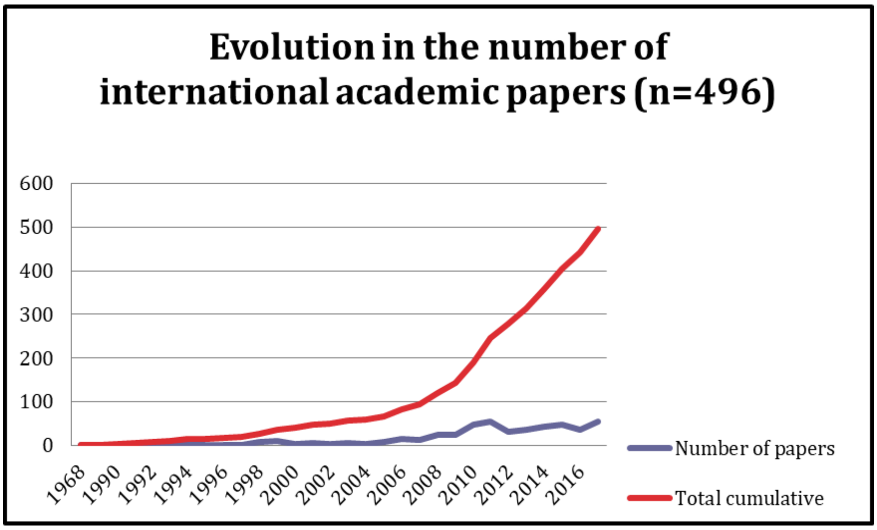
This section shows the descriptive results obtained from the 496 articles from the Scopus database, for the period 1968- 2017 covered by this research.

1.5.1. Evolution of published papers

Figure 1.2 shows the evolution of the final selection of international academic articles (n=496) that have been selected following an exhaustive SLR.

In particular, during the decade of 2008-2017, the number of publications has increased significantly, representing 83.50% of total analyzed. This total reflects the growing importance of the topic studied in recent years.

Figure 1.2: Evolution in the number of international academic articles during the years 1968-2017



As it also can be seen, during the years 1968-1999, there were very few articles published. It can be observed that there is a growing trend in terms of number of papers published since year 2000. Also, after the 2008 worldwide financial crisis, researchers started to explore much more this field of study achieving a dramatic increase in scientific publications.

1.5.2. Most frequently cited papers in Scopus

Table 1.9 provides information on the most frequently-cited articles, considering the authors, the title, and the year of publication, as well as the total number of citations obtained after the publication. The most cited article is published by Altman in 1968, titled “financial ratios, discriminant analysis and the prediction of corporate bankruptcy”, with 3461 citations in total. The second ranked paper is written by Tam and Kiang (1992), which obtained 595 citations.

Table 1.9: Most frequently cited academic articles base on the systematic literature review

	Authors	**Title**	**Year of publication**	**Total citations**
1	Altman	Financial ratios, discriminant analysis and the prediction of corporate bankruptcy	1968	**3461**
2	Tam and Kiang	Managerial applications of neural networks: The case of bank failure predictions	1992	**595**
3	Pan	A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example	2012	**364**
4	Altman et al.	Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience)	1994	**360**
5	Hillegeist et al.	Assessing the probability of bankruptcy	2004	**348**
6	Wilson and Sharda	Bankruptcy prediction using neural networks	1994	**332**
7	Fletcher and Goss	Forecasting with neural networks. An application using bankruptcy data	1993	**217**
8	Balcaen and Ooghe	35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems	2006	**196**
9	Beynon and Peel	Variable precision rough set theory and data discretization: An application to corporate failure prediction	2001	**189**
10	Lee et al.	Hybrid neural network models for bankruptcy predictions	1996	**141**

As shown in the table 1.9, a set of authors demonstrated the importance of bankruptcy prediction and its close connection with the corporate world. It should be mentioned that, among the first ten papers under the aforementioned criteria of ranking, six papers are based on the neural network theory (except the first one, which used multivariate discriminant analysis; the ninth one, which used rough set and the fifth and eighth ranked papers, which are overview studies).

1.5.3. Most productive and cited journals

The authors analyzed which journals are the most productive and most frequently-cited in this research field, considering the 496 obtained from the systematic literature review and their corresponding ranking.

Table 1.10: The most productive and most frequently cited journals according to the systematic literature review

Ranking	Journal name	Number of articles in this study	Number of citations	Impact factor 2016
1	The Journal of Finance	1	3461	5.290
2	Knowledge-Based System	21	1030	4.529
3	Decision Support Systems	12	913	3.222
4	Journal of Banking and Finance	9	780	1.776
5	Management Science	2	628	2.822
6	Omega	7	454	4.029
7	Review of Accounting Studies	5	481	1.756
8	Information and Management	2	240	3.317
9	British Accounting Review	3	234	2.135
10	Journal of International Money and Finance	2	133	1.853
Total number of articles published by top 10 ranking journals		64		

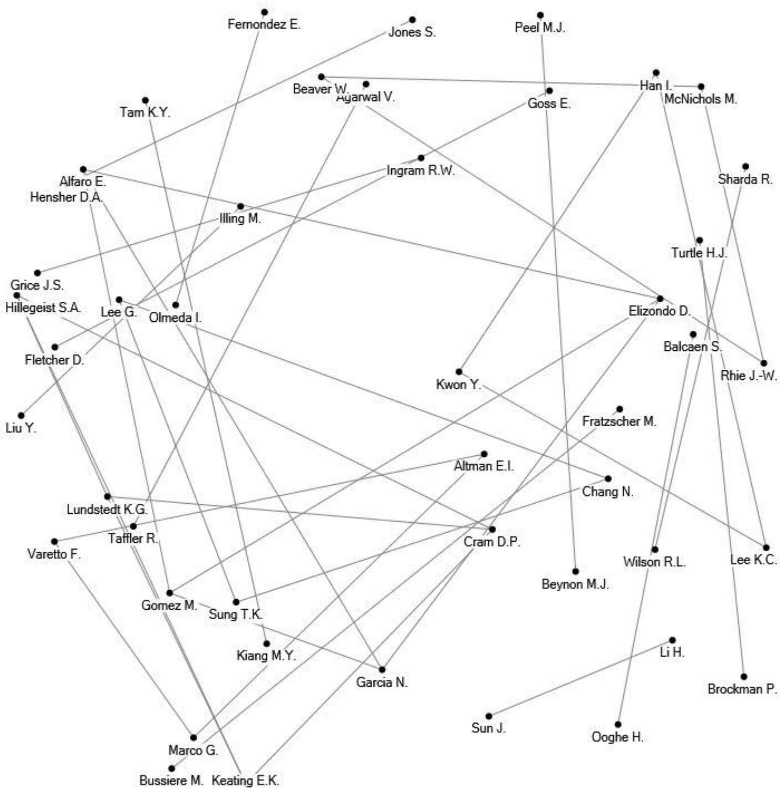
Table 1.10 shows the top ten most productive journals of all the journals that have been collected in this literature review. These 10 journals in the ranking published 12.9% (64 of 496 papers) of the total set of papers included in this study, which means that the research topic is dispersed and distributed in a large number of different journals.

It is worth mentioning that the first ranked journal, The Journal of Finance, has the highest number of citations in this research filed mainly due to the publication of Altman (1968). While the second ranked journal is the one that published most papers (21 of total 64 papers, representing 33% in the top 10 ranking list), with a total citation of 1030 which is much lower than the first ranked one. The authors also notice that there is a huge difference in terms of number of papers published from the top 1 ranked journal to the top 10 since the tenth ranked journal only published 2 papers with 133 citations which accounts for 3% of the total citations from the first ranked journal (3461 citations).

1.5.4. Relationship among authors (co-authorship)

In order to demonstrate collaborations among the different authors belong to the selected set of articles as part of the SLR, a co-authorship has been created with the application of NodeXL, an analysis tool specialized in interactive social network visualization. It should be mentioned that, only the authors of the first 25 most frequently-cited papers have been considered due to the huge number of papers collected in our literature (496 papers). Therefore 45 authors were considered for the analysis of co-authorship in this study.

Figure 1.3: Co-authorship among the authors (Created by the authors, using NodeXL)



As shown in the map, during the evolution of the time considered in the study, the investigating activities were carried out separately, as in a group of authors there are only two or three, occasionally four researchers working together and barely with connection to other groups.

Therefore, it can be detected that there is low degree of collaborations among authors, as there is little density in the co-authorship map (with graph density 3.6%), showing that the main researchers were not working together closely in the past years in this study.

1.5.5. Most popular methods & models studied by authors

Reviewing the title, abstract and keyword of the sample (496 papers), we addressed some primary methods and models that have been applied or studied since 1968. It is observed that, not all 496 papers reflected the model type that are used or studied in their title, abstract or keywords. In this case, there are 175 papers that haven not mentioned and applied any models upon the aforementioned criteria. Thus, the information that we have obtained will be based on the rest of the sample: 321 papers. It is also worth mentioning, as the fact of that one paper can use or analyze more than one model, the sum of all the result doesn’t have to be 321 papers exactly.

Among all the primary models and methods, it can be divided generally into two groups: statistical and machine learning. We conduct a ranking (see Table 1.11&1.12) according to each group, which is shown as below:

Table 1.11: Ranking of classical statistical models

CLASSICAL STATISTICAL MODELS		
Ranking	Method & model name	Number of papers
1	Logistic regression (Logit)	123
2	Discriminant analysis	52
3	Multivariate Discriminant analysis & Z-score	33
4	Hazard	19
5	Logit and probit	7
6	Probit	6

Table 1.12: Ranking of machine learning and artificial intelligence models

MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE MODELS		
Ranking	Method & model name	Number of papers
1	Neural Network	56
2	Support vector machine	32
3	Decision tree	21
4	Genetic algorithm	20
5	Fuzzy	17
6	Rough set	13
7	Data mining	11

As it can be seen in the Table 1.11 and Table 1.12, the most frequently used and studied model in the corporate bankruptcy prediction area is the classical statistical model: Logistic Regression, or also known as logit model, that 123 out of 321 papers are related to this model, representing 38.3% of the total sample. The second most frequently applied model is the artificial intelligence model: Neural Network, with 56 papers applied and representing 17.5% of total sample. Discriminant analysis model ranked as the third with 52 papers. The fourth and fifth ones are MDA & Z-score (33 papers) and Support Vector Machine (32 papers). Among the first five primary models in this area, three of them are statistical and two of them are of artificial intelligence & machine learning area, pointing out that the latter has just become more popular, thanks to the emerging technologies and development of computer science and artificial intelligence in the recent years.

We have also detected some other newly applied machine learning models which appeared after year 2007 listed as below in Table 1.13:

Table 1.13: Ranking of other machine learning models

OTHER MACHINE LEARNING MODELS		
Ranking	**Method & model name**	**Number of papers**
1	**Adaboost**	**7**
2	**Case-based reasoning**	**6**
3	**Particle swarm optimization**	**5**
4	**K-nearest neighbor**	**5**
5	**Random forest**	**5**
6	**Naïve Bayes classifier**	**3**

Although those newly emerged machine learning models are not applied very frequently at the moment, we can still detect the trend of the increasing interest on innovative models, due to the fact that big data application is becoming more and more essential in the 21th century.

1.6. Discussion and conclusions

The first conclusion that we can address is that the bankruptcy prediction research topic is one of growing interest, especially after 2008 global financial crisis. Due to the fact that there is no precise definition of business failure, the establishment of keywords for searching the related core papers has been carried out by considering maximally the related descriptive words, such as default, insolvency, bankruptcy, etc.

After the preliminary search using Scopus database, during the period of 1968-2017 the most frequently cited article was published by Altman in 1968, with a total number of 3461 citations which keeps the highest record of citations compared to other authors. Among the ten most frequently cited papers, six of them applied neural networks as their primary theory for research. The most productive journal is Knowledge-based System due to the highest number of articles published (n=21) in this research area, while the journal with most citations is The Journal of Finance, mainly due to the publication of Altman's work in 1968 that achieved a great number of citations.

Through a network analysis using NodeXL, it is allowed to obtain a co-authorship map of the different authors that had been shown as result of the SLR. It was revealed that the collaboration among the main authors is weak, as they tend to work alone or in small groups and with little connection to other authors or groups when publishing studies.

We also analyzed the model and method that are applied and studied primarily in this area. The Logistic Regression (Logit) and Neural Network are the two most representative models of statistical models and artificial intelligence & machine learning models adopted in this field of research.

Finally, the possible lines of future research are as follows:

- Further compare different models applied in the past bankruptcy prediction studies and the accuracy rate so as to draw conclusions correspondingly.
- Apply some bankruptcy prediction models to sectorial studies with empirical data so as to verify the viability of modelling

Chapter 2

2. A BIBLIOMETRIC STUDY ON INTELLIGENT TECHNIQUES OF BANKRUPTCY PREDICTION FOR CORPORATE FIRMS

Overview: Bibliometric analysis is an effective method to carry out quantitative study of academic output to address the research trends on a given area of investigation through analysing existing documents. This paper aims to explore the application of intelligent techniques in bankruptcy predictions so as to assess its progress and describe the research trend through bibliometric analysis over the last five decades. The results indicate that, although there is a significant increase in publication number since the 2008 financial crisis, the collaboration among authors is weak, especially at the international dimension. Also, the findings provide a comprehensive view of interdisciplinary research on bankruptcy modelling in finance, business management and computer science fields.

The authors sought to contribute to the theoretical development of bankruptcy prediction modeling by bringing new knowledge and key insights. Artificial intelligent techniques are now serving as important alternatives to statistical methods and demonstrate very promising results. This paper has both theoretical and practical implications. First, it provides insights for scholars into the theoretical evolution and intellectual structure for conducting future research in this field. Second, it sheds light on identifying under-explored machine learning techniques applied in bankruptcy prediction which can be crucial in management and decision-making for corporate firm managers and policy makers.

Keywords: bankruptcy prediction, business failure, bibliometric, artificial intelligence, financial distress, insolvency.

JEL codes: G10, G33, M21

2.1. Introduction

Over the past 50 years, bankruptcy prediction has been a field of increasing interest to researchers all around the world. Many academic studies have been dedicated to exploring the corporate failure prediction model with better accuracy. Since the breakthrough in the bankruptcy prediction model was introduced by Altman in 1968, a large body of research has focused on the prediction of corporate financial distress. In most cases, authors tend to use the ultimate failure (bankruptcy) as the dividing line when they distinguish between failed and non-failed firms.

Since different sectors require different bankruptcy prediction models, researchers use distinctive methods and variables to construct models for each sector. The diversity on this subject led to the appearance of some influential comparative and review studies (Ravi Kumar and Ravi 2007; Balcaen and Ooghe 2006; Dimitras et al. 1996; Gissel et al. 2007). However, most of these review studies focus on statistical method-based models. Meanwhile, along with the development of computer science and artificial intelligent technology, some researchers started to apply machine learning techniques to the construction of bankruptcy prediction models (Pan 2012; Min and Lee 2005; Shin et al. 2005; Wilson and Sharda 1994; Zhang et al. 1999). Do Prado et al. (2016) pioneered to adopt bibliometric analysis to identify the use of multivariate techniques in bankruptcy research. Some others compare particularly two or three machine learning techniques for bankruptcy prediction modeling (Jo et al. 1997; Alfaro et al. 2008; Boyacioglu et al. 2009). However, to the best knowledge of the authors, there is no comprehensive bibliometric analysis studying the evolution of artificial intelligent techniques application in bankruptcy prediction and the authors sought to fill the gap in this area of research. The rationale for this paper lies in its recognition that this research field has been expanding dramatically in recent years and it is important to assess its progress and describe the research trend through bibliometric analysis and visualization.

Given the importance of this topic, the current study aims to explore the existing academic literature regarding bankruptcy predictions using intelligent techniques and the specific objectives are as follows:

1. To describe how this area of research is organized and progressed in terms of publications, authors, and journals, and identify the bibliometric trends (co-authorship, geographical area of authors, co-citation, co-occurrence and text mining, etc.) of bankruptcy prediction applying intelligent techniques.
2. To present an overview study bringing together research work classified in business, finance and management fields with the computer science field so as to have a multidisciplinary research in bankruptcy prediction modelling.
3. To discuss, based on results and knowledge obtained, the under-explored areas and reflect on possible future research opportunities to gain a more profound insight and understanding of this research topic.

This study has been conducted based on relevant search using the Web of Science database from 1968 (the year when Altman published the Z-score model) to 2018. Eighteen keywords (6 primary and 12 secondary) are identified to carry out the literature search and the sample consists of 413 academic publications in this study. The bibliometric approach contributed significantly to exploring and describing the existing academic literature on bankruptcy prediction modelling.

This chapter is structured as follows. Section two starts with the literature review of bibliometric studies and bankruptcy prediction so as to collect principal methods that have been widely used by authors. Section three presents the research methodology based on the bibliometric approach and descriptive data analysis. The main research findings are discussed in section four. Conclusions, limitations and future research are presented in section five.

2.2. Literature review of bibliometric study and bankruptcy prediction

The term *bibliométrie* was first used by Otlet (1934). He defined it as “the measurement of all aspects related to the publication and reading of books and documents.” Pritchard (1969) introduced firstly the anglicized version *bibliometrics*, defining it as an area of study that applies mathematical and statistical methods to examine and quantify books and other media of communication. Historically, bibliometric methods have been used to trace relationships among academic journal citations (Schaer 2013). Nowadays, it can also be applied in quantitative research assessment exercises of academic output in order to address the trends on a given area of study, through analyzing existing documents, such as books, reports, theses, dissertations, published articles, etc. More specifically, the bibliometric studies aim to detect the intellectual networks among scholars or identify and map the intellectual structure of an area of study (Pinto et al. 2014).

Bibliometric studies may examine an array of different objects and have been used in different disciplines, such as information systems, knowledge management, marketing, innovation, entrepreneurship, etc. (Pinto et al. 2014). In the research field of bankruptcy prediction, do Prado et al. (2016) conducted a bibliometric study on the knowledge field of credit risk and bankruptcy, with the purpose of identifying and describing the use of multivariate data analysis techniques, as well as presenting the publications tendencies, the outstanding journals, the authors and their structures of co-citation and co-authorship. Klopotan et al. (2018) provided knowledge and key insights into the bibliometric research trends in the area of early warning systems in management, economics, public administration and business finance fields.

Since there is an increasing number of papers published related to business failure prediction in the recent years, some other authors shed light on carrying out comparative studies or provide overviews of business failure prediction models. Hillegeist et al. (2004) compared two accounting-based models, Altman’s

(1968) Z-score and Ohlson's (1980) O-score, with a market-based measure they developed based on the Black-Scholes-Merton option-pricing model, showing that the latter can provide significantly more information than the former two. Kim (2011) compared the functional characteristics of multivariate discriminant analysis, logistic, artificial neural network and support vector machine models by analysing their overall classification, prediction accuracy and relative error cost ratios. He concluded that an artificial neural network was the most recommended technique for the Korean hotel sector due to its high accuracy and small relative error costs. De Llano Monelos et al. (2016) compared the effectiveness of eight popular prediction methods, pointing out that different methodologies used in each study did not show significant influence on the results, and they suggested focusing on improving the quality of informational context of variables rather than designing sophisticated analysis techniques. Jabeur and Fahmi (2017) compared two financial distress prediction statistical methods (discriminant analysis and logistic regression) with the machine learning model (random forest), concluding that random forest is the most robust and efficient method with better results.

As for the overview studies, Dimitras et al. (1996) conducted a survey of literature on business failure, introducing a new framework to discuss the findings. This new framework includes classification of studies by country, method and industrial sector. Balcaen and Ooghe (2006) undertook an overview of classic statistical methodologies during the last 35 years (1969-2004), seeking to understand their features as well as their related problems. Ravi Kumar and Ravi (2007) presented a review on bankruptcy prediction in banks and firms based on statistical and intelligent techniques during 1968-2005, highlighting the source of data sets, financial ratios used, country of origin, time line of study and accuracy comparison of each technique. Gissel et al. (2007) analyzed 165 bankruptcy prediction studies published during 1965-2007 aiming to reveal trends in model development based on different methods, number and variety of factors, and specific uses of models.

In the literature related to intelligent techniques used in bankruptcy prediction, Tam (1991) believes that a neural network is a competitive instrument for evaluating the financial condition of a bank, so his study contributes a discussion regarding the potential and limitation of a neural network as a general modeling tool for financial applications. Min and Lee (2005) state that a number of studies have shown that machine learning techniques achieved better performance than transitional statistical ones. They intend to suggest a new bankruptcy prediction model with better explanatory power and stability by applying a support vector machine. After comparing with multiple discriminant analysis, logistic regression analysis and three layers fully connected back-propagation neural network, the support vector machine was declared to outperform the other methods. Dimitras et al. (1999) used a rough set to weaken limitations of previous models and confirm that the rough set approach can discriminate between financially healthy and failing firms with encouraging results.

However, none of the previous work has carried out a complete and comprehensive study applying bibliographic and bibliometric methods, in order to analyze and address the evolution of major intelligent techniques-based methods used in the field of bankruptcy prediction. Therefore, this paper contributes to the existing literature by studying and analyzing the evolution of machine learning techniques in bankruptcy predictions so as to provide new academic and empirical insights. Moreover, it adopts an inclusive research criterion (not limiting itself to a specific discipline or group of journals) aiming to obtain a more comprehensive picture of research on bankruptcy prediction modelling.

2.3. Research methodology and descriptive data analysis

The literature searching covers the journal articles and reviews from the database of Web of Science (core collection) published during 1968-2018. Initial search for identifying the international academic papers related to the research topic were carried out by using a set of keyword combinations as searching criteria. Such criteria is based on a previous systematic literature review conducted by the authors (Shi and Li 2019) providing the following combination of primary keywords: **Bankruptcy Prediction** (Altman et al. 1994; Hillegeist et al. 2004; Wilson and Sharda 1994; Fletcher and Goss 1993; Lee et al. 1996, Serrano-Silva et al. 2018); **Default Prediction** (Tserng et al. 2014; c et al. 2011); **Financial Failure** (Altman and Hotchkiss 2006); **Financial Distress** (Pan 2012; Jones and Hensher 2004; Sun and Li 2008; Xiao et al. 2012); **Insolvency** (Langford et al. 1993; Lepetit and Strobel 2013; Jackson and Wood 2013); and **Business Failure** (Dimitras et al. 1996).

Given the aforementioned search criteria, the authors have consulted numerous previous studies (Ravi Kumar and Ravi 2007; Dimitras et al. 1996; Gissel et al. 2007) in order to set the scope of the intelligent techniques used for bankruptcy prediction and the most frequently applied artificial intelligent techniques are: neural network, support vector machine, decision tree, genetic algorithm, fuzzy, rough set, data mining, case-based reasoning, DEA (data envelopment analysis), Adaboost, K-nearest neighbors, Bayesian network. Therefore, the combination of searching keywords design is displayed in Figure 2.1.

Figure 2.1: Combination of searching keywords

Title		Topic
Bankruptcy prediction		Neural network
OR		**OR**
Default prediction		Support vector machine
OR		**OR**
Financial failure	**AND**	Decision tree
OR		**OR**
Financial distress		Genetic algorithm
OR		**OR**
Insolvency		Fuzzy
OR		**OR**
Business failure		Rough set
		OR

	Data mining **OR** Case-based reasoning **OR** DEA (data envelopment analysis) **OR** Adaboost **OR** K-nearest neighbors **OR** Bayesian network
Field term	**intelligent techniques**

The searching process has been carried out by introducing the established keywords, where field terms are used in TITLE searching and intelligent techniques keywords are applied in TOPIC searching, and the two are combined with the connective word AND. After introducing such keywords, results are refined by considering only scientific articles and reviews. As for language options, none of the languages has been delimited, although the majority of results are written in English. No filter on disciplines is placed since the authors sought to provide a comprehensive view of research undertaken across distinct disciplines. The search is restricted to the period 1968 (when the first paper of bankruptcy prediction was published) to 2018. After screening out the duplicates and irrelevant papers, the final retrieved results are 413 international academic papers.

2.3.1. Overview of statistical and intelligent-based technique methods in bankruptcy prediction

Referring to bankruptcy prediction models, two families of techniques are generally applied as statistical techniques and artificial intelligent/soft computing techniques. Altman (1968) pioneered to use the statistical method as multivariate discriminant analysis to forecast business failure. Since then, the statistical approach has been majorly applied for the development of bankruptcy prediction models. Neural network as intelligent technique has been adopted widely after 1990s (Tam, 1991; Lee et al. 1996). Ravi Kumar and Ravi (2007) concluded logistic regression and discriminant analysis as statistical techniques. They also covered neural network, decision tree, case-based reasoning, rough sets, data envelopment analysis, support vector machine and fuzzy logic as intelligent techniques in their review study.

Reviewing a large number of studies published during 1968-2018, where various statistical and intelligent techniques were applied to solve bankruptcy prediction problems in different sectors including manufacturing and industrial firms, banks, etc., the authors contribute to elaborating a summary of models that are based on the aforementioned two methods (see Table 1).

Table 2.1: Summary of models based on statistical methods & intelligent techniques

STATISTICAL METHODS	
logistic regression/logit:	Makeeva and Khugaeva 2018; Cohen et al. 2017; Yerdelen et al. 2016; Xu et al. 2014; Chen 2011; Premachandra 2009; Lawrence et al. 2009
Probit	Kovacova and Kliestik 2017; Ahmadpour-Kasgari et al. 2012
Discriminant analysis	Altman 1968; Deakin 1972; Xie et al. 2010
Hazard model	Eling and Jia 2018; Tudor et al. 2015; Dang 2013
Partial least squares	Serrano-Cinca and Gutiérrez-Nieto 2013; Ben Jabeur 2017

INTELLIGENT TECNIQUES	
Neural network	Atiya 2001; Tam 1991; Lee et al. 1996.
Support Vector Machine	Min and Lee 2005; Shin et al. 2005; Li and Sun 2009; Li and Sun 2011; Li et al. 2014; Lee et al. 2011
Data Mining	Sun and Li 2008; Yerdelen et al. 2016; Geng et al. 2015
Decision Tree	Gepp et al. 2009; Kim and Upneja 2014; Chen 2011
Genetic algorithm	Shin and Lee 2002; Varetto 1998; Gordini 2014
Rough set	Dimitras et al.1999 ; Ahn et al. 2000
Fuzzy logic	Chen et al. 2009; Chou et al. 2017; Georgescu 2017
Case-based reasoning	Park and Han 2002; Li and Sun 2009; Li and Sun 2009; Li and Sun 2008
DEA (data envelopment analysis)	Shetty et al. 2012; Huang et al. 2015; Yeh et al. 2010
Adaboost	Zhou and Lai 2016; Alfaro et al. 2008; Sun et al. 2011
K-nearest neighbors	Chen et al. 2011; Li et al. 2009
Bayesian network	Sun and Shenoy 2007; Wang et al. 2017

Meanwhile, there are also authors who applied more than one method to establish a bankruptcy prediction model. These methods are presented as hybrid methods. Wang et al. (2017) applied the hybrid of logistic regression and Bayesian probabilistic networks to establish a bankruptcy prediction model. Li and Sun (2011) proposed a hybrid method integrating principal component analysis with multivariate discriminant analysis and logit. Cao and Chen (2013) presented a fuzzy membership for the fuzzy support vector machine combined with case-based reasoning for predicting financial distress of Chinese listed companies. Lin et al. (2011, 2013) designed a hybrid business failure prediction model using locally linear embedding, an isometric feature mapping algorithm and a support vector machine to predict financial failure of firms in different sectors. Other authors (Yeh et al. 2010; Min et al. 2006) also contributed by applying a hybrid approach combining support vector machines for business failure and bankruptcy prediction.

2.3.2. Top 10 most productive international journals and total citations (according to number of publications)

As shown in Table 2.2, the journal *Expert Systems with Applications* is ranked first due to the large number of publications (87 papers) in the corresponding area (3.78 times more than the second ranked journal, occupying 21.07 % of the total 413 papers in this study), with a total of 4484 citations. The second ranked journal is *European Journal of Operational Research* with 23 papers and 1857 citations followed by the third ranked journal *Knowledge-Based Systems* with 1068 citations. Two journals share the eighth position as they have the same number of published papers (5 papers), but it is worth mentioning that the journal *Computers & Operations Research* shows the lowest number of citations (7 citations). Five journals share the tenth position (4 papers) with different levels of citations. Although the journal *Omega-International Journal of Management Science* has published only 4 papers, it has gained 265 citations. To conclude, it can be observed that, although some journals (as *Omega-International Journal of Management Science* and *Journal of Testing and Evaluation*) have fewer number of publications, they have achieved great influence in the field of bankruptcy research.

Table 2.2: Top 10 most productive international journals and total citations

	Name of journals	Number of publications	Total citations
1	Expert Systems with Applications	87	4484
2	European Journal of Operational Research	23	1857
3	Knowledge-Based Systems	22	1068
4	Applied Soft Computing	12	368
5	Decision Support Systems	11	638
6	Neurocomputing	10	349
7	Journal of Forecasting	9	183
8	Journal of Testing and Evaluation	5	219
8	Computers & Operations Research	5	7
10	Omega-International Journal of Management Science	4	265
10	Information Sciences	4	174
10	International Review of Financial Analysis	4	57
10	Journal of The Operational Research Society	4	39
10	Romanian Journal of Economic Forecasting	4	21

2.3.3. Top 10 most-cited papers of intelligent techniques-based models

To identify the most influential papers in the field of bankruptcy prediction using intelligent techniques, the top 10 most-cited papers have been collected in Table 2.3 in terms of author's name, title, year of publication and number of citations.

Table 2.3: Top 10 most-cited international papers

	Author's name	Title	Year	Citation
1	Ravi Kumar, P.; Ravi, V.	Bankruptcy prediction in banks and firms via statistical and intelligent techniques - A review	2007	388
2	Pan, Wen Tsao	A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example	2012	342
3	Min, JH; Lee, YC	Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters	2005	332
4	Shin, KS; Lee, TS; Kim, HJ	An application of support vector machines in bankruptcy prediction model	2005	323
5	Wilson, Rl; Sharda, R	Bankruptcy Prediction Using Neural Networks	1994	285
6	Zhang, GQ; Hu, MY; Patuwo, BE; Indro, DC	Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis	1999	251
7	Dimitras, AI; Slowinski, R; Susmaga, R; Zopounidis, C	Business failure prediction using rough sets	1999	247
8	Atiya, AF	Bankruptcy prediction for credit risk using neural networks: A survey and new results	2001	230
9	Dimitras, AI; Zanakis, SH; Zopounidis, C	A survey of business failures with an emphasis on prediction methods and industrial applications	1996	222
10	Min, SH; Lee, J; Han, I	Hybrid genetic algorithms and support vector machines for bankruptcy prediction	2006	204

Four of the most cited papers were published during 1994-2000 and six were published during 2001-2012. Among these ten papers, two of them are review studies (the number 1º and the number 9º). Four of them are about the application of a neural network (the number 2º, 5º 6º 8º) and two of them used a support vector machine (the number 3º and 4º). One (the number 7º) applied the rough set theory and the last one (the number 10º) used a hybrid model combining genetic algorithms and a support vector machine.

Ravi Kumar and Ravi (2007) wrote the first ranked paper with 388 total citations. They analyzed studies during the years 1968-2005 and grouped the statistical methods and intelligent techniques used for bankruptcy prediction into nine families. They mainly focused on comparing the source of data sets, financial ratios used, country of origin, timeline of study and accuracy. The second ranked paper used the Fruit Fly Optimization Algorithm to optimize a general regression neural network stating that it achieves good classification and prediction capability (Pan 2012). The third ranked paper was written by Min and Lee in 2005. They proposed a new support vector machine model and compared it with some models as multiple discriminant analysis, logistic regression analysis and three-layer fully connected back-propagation neural network, concluding that the support vector machine outperforms the other methods.

With respect to the discipline collaboration of authors, the authors of the most cited paper published in *European Journal of Operational Research* are Ravi Kumar and Ravi (2007) and they are both specialized in machine learning techniques and modeling. They published another paper in 2008, entitled "Soft computing system for bank performance prediction" in *Applied Soft Computing Journal* (Ravi et al. 2008). Pan, the author of the second most cited paper (Pan 2012) published in *Knowledge-Based Systems*, is specialized in both the finance and modeling fields. Besides, he has published several modeling papers in the areas of business and finance using intelligent techniques such as genetic programming, fuzzy, data mining, neural network, etc. (Chang et al. 2010; Pan 2010; Mei and Pan 2010; Ming-Te et al. 2012). Min and Lee (2005), the authors of the third most cited paper, published their study in *Expert Systems with Applications Journal*. Both authors are active in finance and modeling, which can be observed in their subsequent paper applying a difference approach (data envelopment analysis) to credit scoring in 2008 (Min and Lee 2008).

2.4. Bibliometric and network analysis results and findings

In order to observe and assess the trends of publications in this field of research, a bibliometric study regarding intelligent techniques-based bankruptcy prediction models was conducted. VOSviewer software was applied to analyze the academic literature and examine the evolution of published papers, co-authorship, geographical area (country/territory) of authors, co-citation, co-occurrence and text mining in this area.

VOSviewer is one of the widely used computer programs that serves as "visualization techniques that can be used to map the ever-growing domain structure of scientific disciplines and to support information retrieval and classification" (Borner et al. 2005). It was chosen because it pays special attention to the graphical representation of bibliometric maps and it specializes in displaying large bibliometric maps in ways that are easy to interpret and comprehend (Waltman et al. 2010).

2.4.1. Evolution of publications related to intelligent techniques in bankruptcy prediction

Figure 2.2: Evolution of publications

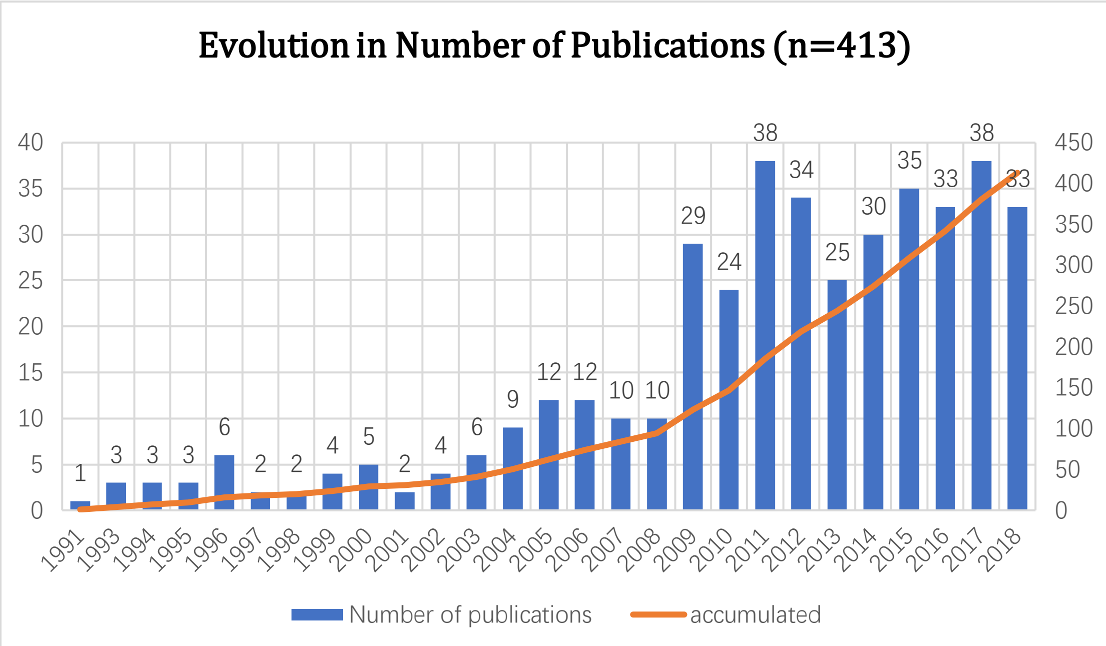


Figure 2.2 shows the evolution in number of publications of intelligent techniques-based models. Comparing with the breakthrough statistical method-based article published by Altman in 1968, the first intelligent technique model was recorded in 1991 and the number of papers initially increased very slowly in the following 17 years until the 2008 global financial crisis. It can be observed that there was a significant increase during 2008-2009, as the number of papers increased from 10 to 29. From then on, interest in the bankruptcy prediction research field grew rapidly, which aligns with the findings obtained by do Prado et al. (2016). The peaks, in terms of the number of papers published were recorded in the years 2011 and 2017 (38 papers in each year, respectively).

2.4.2. Individual and country co-authorship analysis

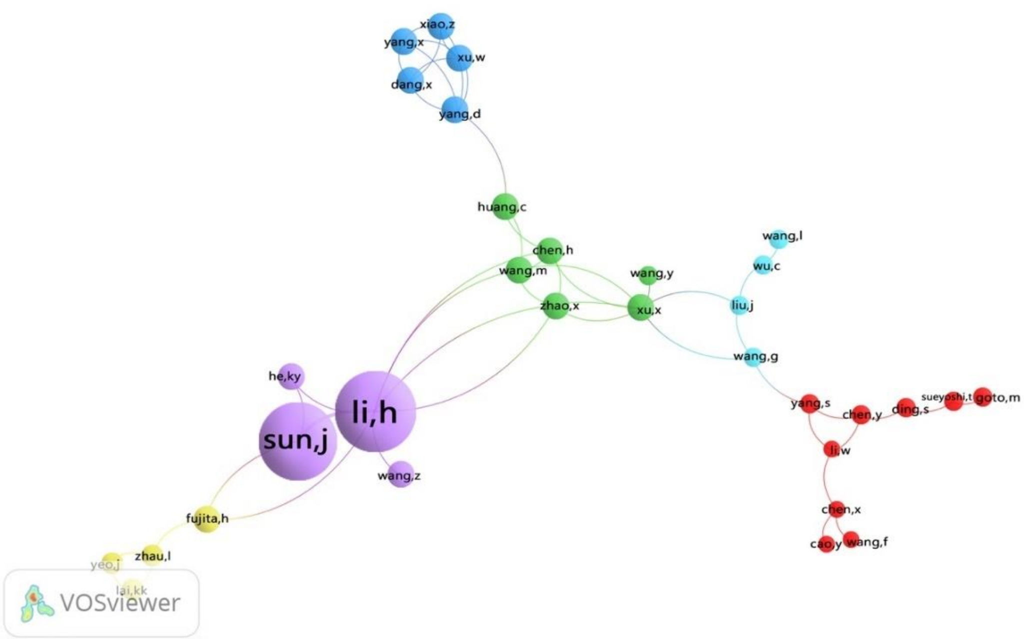
Co-authorship research is an important content of bibliometric studies and the level of collaboration is an index to access the status of research in a specific field (Reyes et al. 2016). In this section, it helps to address the collaborative strength and research groups of intelligent technique users in the field of bankruptcy prediction, from the perspectives of individuals and countries.

It is worth defining the difference between the concept of co-authorship and co-citation before moving forward with the interpretation of network of both. Co-authorship analysis aims to investigate the level of research collaborative strength in a specific field (Liao et al. 2018). The term co-author means to write a book, article, report, etc. together with another person or other people (Cambridge University Press 2008). The co-citation occurs when a citing paper cites any work in reference lists. It is a form of document coupling which is defined as the frequency with which two items of earlier literature are cited together by the later literature (Small 1973).

Individual co-authorship analysis

An individual co-authorship network was constructed by the VOSviewer software. For the data selection and thresholds, the minimum number of documents of an author is 3, and the minimum number of citations of an author is 0. Among the 777 authors in total, 32 meet the thresholds and their co-authorship network is shown in Figure 3, where each node represents an author, and the lines and distances reflect the relation among them. The distance between two nodes indicates the intensity of the relation, which means when two nodes are closer to each other, they tend to have a strong relation. Authors who have higher weight, in terms of citations and publications, are represented as larger nodes.

Figure 2.3: Individual co-authorship map



A link is a connection or a relation between two items, and the stronger the link between two items, the thicker the line that is used to display the link in the visualization of the map. In Figure 2.3, links refer to the co-authorship links between researchers. Each link has a strength, indicating the number of publications that two researchers have co-authored (Van Eck and Waltman 2019). The link strength can be used as a quantitative index to depict the relationship between two items and the total link of a node is the sum of link strengths of this node over all the other nodes (Pinto et al. 2014).

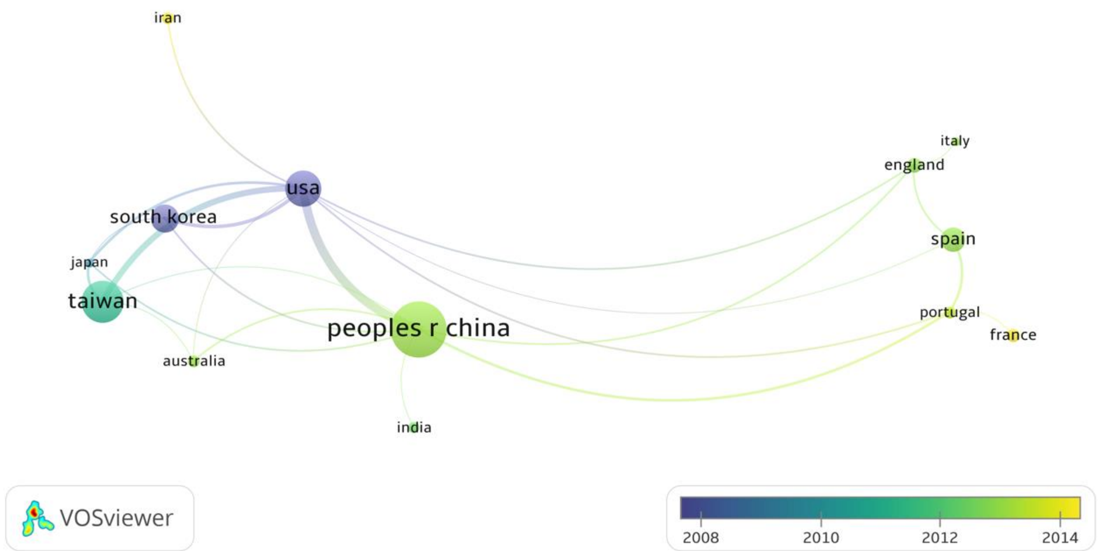
As shown in Figure 2.3, there are six clusters represented by 6 colors. It can be noticed that the largest two nodes for Li and Sun show the highest weight of citations and total link strength. The rest of the authors display significantly lower weight of citations and publications and less collaboration links, as clusters are distributed separately, and one cluster is barely connected to another. It shows the high concentration in the co-authorship network connected with Li and Sun and a huge difference in terms of the total link strength from the rest of the authors.

Comparing co-authorship analysis in different disciplines, there is no consensus achieved regarding the extent of collaboration networks of researchers. Samitas and Kampouris (2018) analyzed the co-authorship in the field of finance in general and indicated that the collaboration network of authors in the financial market area is greatly integrated. Similarly, Newman (2001) used computer science database and found intensive collaboration in this area as well. Nevertheless, Ortega (2014) analyzed the structural co-authorship network, indicating that Mathematics, Social Sciences and Economics & Business present a disperse and little collaborative network, while Physics, Engineering and Geosciences show intense and concentrated networks. In the context of bankruptcy prediction, Shi and Li (2019) carried out the co-authorship analysis without specifying the use of techniques and found low density in a collaboration network among the main researchers, which aligns with the obtained results of this paper. Thus, the authors observed that the collaboration in this interdisciplinary study (business, finance and modelling) is weak among authors, which displays a pattern that is not similar, as suggested by the literature in either finance or modelling disciplines (Samitas and Kampouris 2018; Newman 2001).

2.4.3. Country co-authorship analysis

Country co-authorship analysis is an important form of co-authorship analysis, as it can reflect the degree of communication among countries and the most influential countries in a research field (Liao et al. 2018). A country co-authorship network overlay visualization map has been elaborated and shown in Figure 4. For the data selection and thresholds, the minimum number of documents from a country is 10 and the minimum number of citations from a country is 0. Among the 52 countries, there are 13 that meet the thresholds. It is worth mentioning that the overlay visualization is according to the average publication year, where the colors of items are determined by the score ranging from blue (lowest score) to yellow (highest score).

Figure 2.4: Country co-authorship overlap visualization map



As we can see in Figure 2.4, there are several big nodes on the map that indicate countries and regions with the largest number of publications: China, the USA, Taiwan area, South Korea and Spain. Research centers with the highest number of total links in this field are the USA and China. It should be stated that on this map, the size of a node depends on the number of publications. That is to say, although the USA is not presented as the largest node on the map, it has the highest total link strength for the widest connection and collaboration with various countries and regions of different continents. Spain has the largest node in Europe and is linked closely with other European countries, such as England, France and Portugal. This observation displays that being geographically close tends to enhance the authors' cooperative and collaboration relationship in this area of study.

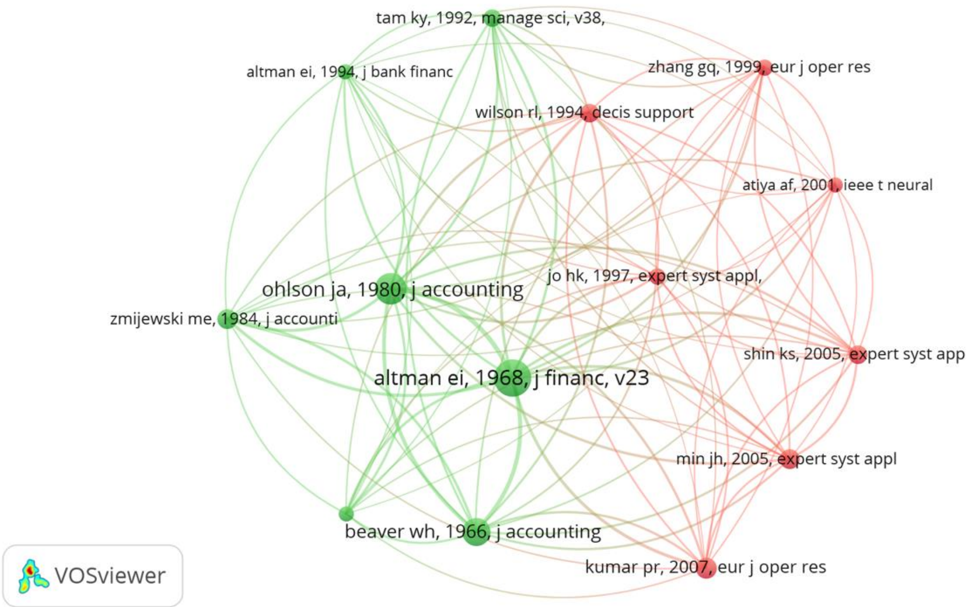
Regarding the average publication year as displayed in Figure 4, both Iran and France (colored yellow) present a high volume of publications after 2014, which may indicate scholars in these two countries show an increasing interest in this research topic in the most recent years. Both the USA and South Korea (colored blue) exhibit a peaking publication trend before year 2008, which may reveal their historical contribution and importance to this field. China, Australia, India and other European countries (colored green) show a notable increasing number of publications between 2010-2012, which confirmed the discovery of an immediate growing trend in the number of publications after the 2008 financial crisis in this field (Yu et al. 2010; do Prado et al. 2016).

2.4.4. Reference Co-citation analysis

Co-citation is a form of document coupling which is defined as the frequency with which two documents are cited together by other documents (Small 1973). A co-citation map consists of a set of nodes representing journal articles and a set of edges representing the co-occurrence of nodes and/or articles in the reference list of papers of that map (Fahimnia et al. 2015). Therefore, the authors conducted the co-citation analysis accordingly regarding the literature on intelligent techniques for bankruptcy prediction.

A reference co-citation map based on bibliographic data was created in VOSviewer (see Figure 5) and the minimum threshold setting for number of citations of an author has been set at 65, a threshold that only 14 of the 9496 authors meet.

Figure 2.5: Reference co-citation map



In Figure 2.5, the authors find that the largest node is Altman (1968), whose paper entitled ¨Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy¨ firstly introduced the multivariate analysis known as Z-score. It has 286 co-citations, which means that among the total literature regarding bankruptcy prediction using intelligent-based techniques (413 papers), 70% of them have cited this article. As a result, it has the strongest total link strength. The second largest node is Ohlson (1980). He created an O-score for bankruptcy prediction as an alternative to the Altman Z-score. The third ranked study is the article published by Beaver in 1966, in which he used univariate analysis to study the ratios in order to test their predictive ability for classifying failed and non-failed firms. The second and third ranked paper (Ohlson 1980; Beaver 1966) have fewer citations and total link strength compared with the first one, but the impact in terms of co-citation is still influential. It can be noticed that among the top 14 studies in the ranking list, all had been published before 2008, which indicates that most papers published during the last ten years (after 2008) have not generated great impact in this research field.

2.4.5. Journal co-citation analysis

The journal co-citation analysis can reveal the overall structure of the subject and the characteristics of a journal (Liao et al. 2018). The distance between two journals in the visualization approximately indicates the relatedness of the journals in terms of co-citation links. In general, the closer two journals are located to each other, the stronger their relatedness. The strongest co-citation links between journals are also represented by lines (Van Eck and Waltman 2019). Figure 2.6 shows the journal co-citation network with minimum number of citations of a journal set at 150. Among the 4218 sources, 15 journals meet the threshold. The size of the nodes represents the activeness of the journal and a smaller distance between two nodes represents a higher co-citation frequency.

Figure 2.6: Journal co-citation map

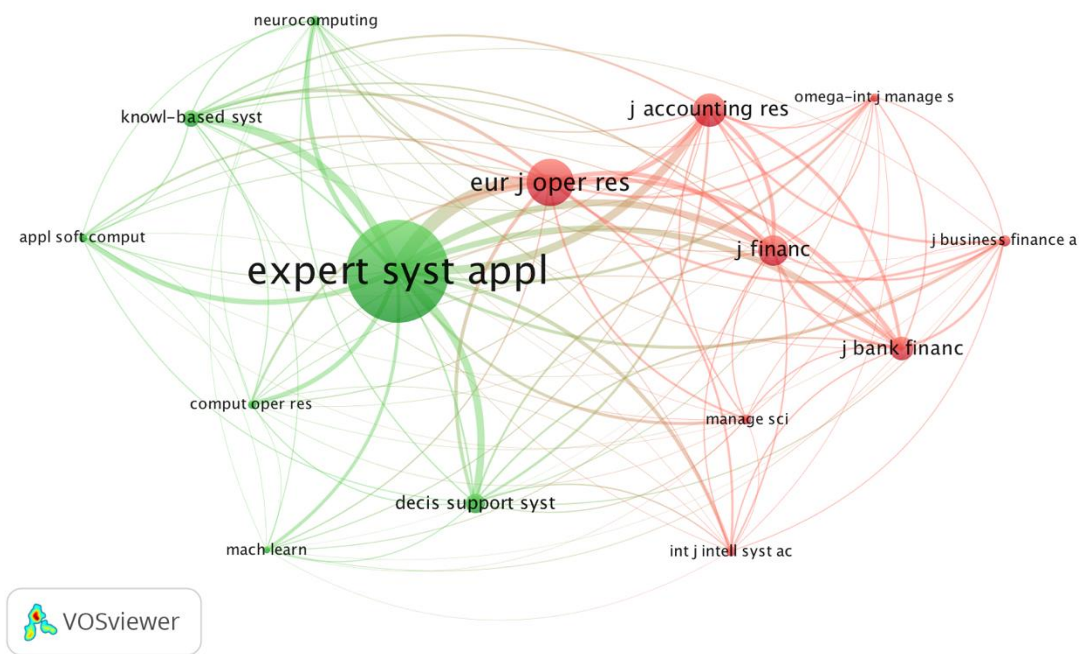


Table 2.4: Top 15 journals with total link strength

(According to co-citation frequency)

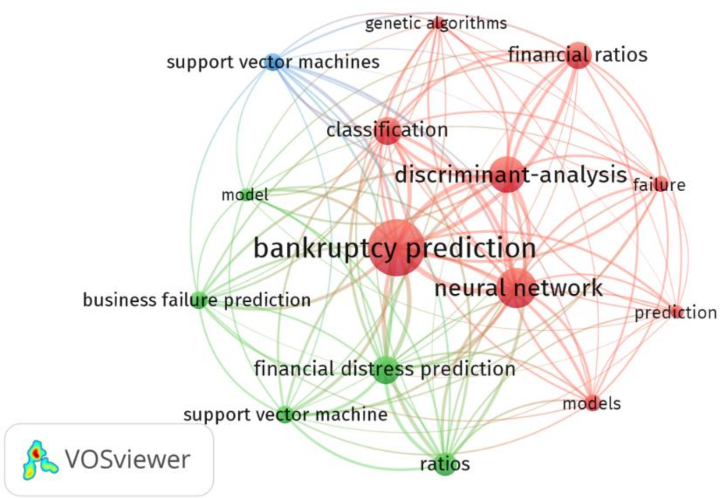
	Name of Journal	Subjects	Co-citation frequency	Total link strength
1	Expert Systems with Applications	Computer science/Engineering	2040	33518
2	European Journal of Operational Research	Decision sciences/ Mathematics	946	19447
3	The Journal of Accounting Research	Business, Management and Accounting/ Economics, Econometrics and Finance	676	12625
4	The Journal of Finance	Business, Management and Accounting/ Economics, Econometrics and Finance	603	10756
5	The Journal of Banking and Finance	Economics, Econometrics and Finance	478	9975
6	Decision Support Systems	Arts and Humanities/ Business, Management and Accounting/ Computer Science/ Decision Science/ Psychology	386	9083
7	Knowledge-Based Systems	Business, Management and Accounting/ Computer Science/ Decision Sciences	352	8707
8	Journal of Business Finance and Accounting	Business, Management and Accounting/ Economics, Econometrics and Finance	244	5654
9	Management Science	Business, Management and Accounting/ Decision Sciences	199	4206
10	International Journal of intelligent systems in accounting finance and management	Business, Management and Accounting/ Economics, Econometrics and Finance	198	4822
11	Neurocomputing	Computer Science/ Neuroscience	197	4894
12	Applied Soft Computing Journal	Computer Science	186	4825
13	Computers and Operations Research	Computer Science/ Decision Science/ Mathematics	178	4770
14	Omega-International Journal of Management Science	Business, Management and Accounting/ Decision Sciences	167	4233
15	Machine Learning	Computer Science	151	3201

A ranking according to co-citation frequency of these fifteen journals with total link strength is presented in Table 2.4. The number of co-citation frequency is calculated according to the reference list of papers within the same dataset. More specifically, journal co-citation analyzes how many times one journal is cited together with another journal by the same document (Van Eck and Waltman 2019). For instance, the first ranked journal *Expert Systems with Application* was co-cited (be cited together with another journal by one paper) 2040 times. There are two colors distinguishing the two assigned clusters. It can be noticed that the green cluster contains seven nodes, which are mainly within the computer science area. On the other side, the red cluster contains eight nodes. These journals are principally in the areas of business, management and accounting/economics, econometrics and finance/decision sciences. According to the ranking by total link strength and citations, the first journal *Expert Systems with Applications*, which is a computer science and engineering journal, is far ahead of the rest of the journals in terms of both citations and total link strength. Among these fifteen most co-cited journals, the computer science discipline and management and finance discipline have almost equal distribution in terms of number of journals (seven journals and eight journals respectively).

2.4.6. Co-occurrence analysis

The authors construct a map based on a co-occurrence matrix, dividing keywords into three clusters (see Figure 2.7) with the minimum number of occurrences of a keyword set at 30. Among 1288 keywords, 15 meet the threshold; they are presented as 15 nodes. It should be mentioned that, due to the difference in ways that authors describe a term (like plural or single, with or without hyphen), one item that was expressed in distinct ways may be counted separately. In order to obtain more precise results, the authors used the thesaurus function of VOSviewer and successfully combined the different formats of keywords. The keyword “bankruptcy prediction” has the highest occurrence and total link strength. Other keywords with a high occurrence include “neural networks”, “discriminant-analysis”, “financial distress prediction” and “classification”. The node, bankruptcy prediction, displays thick lines connecting with discriminant analysis, financial distress, classification, and neural network.

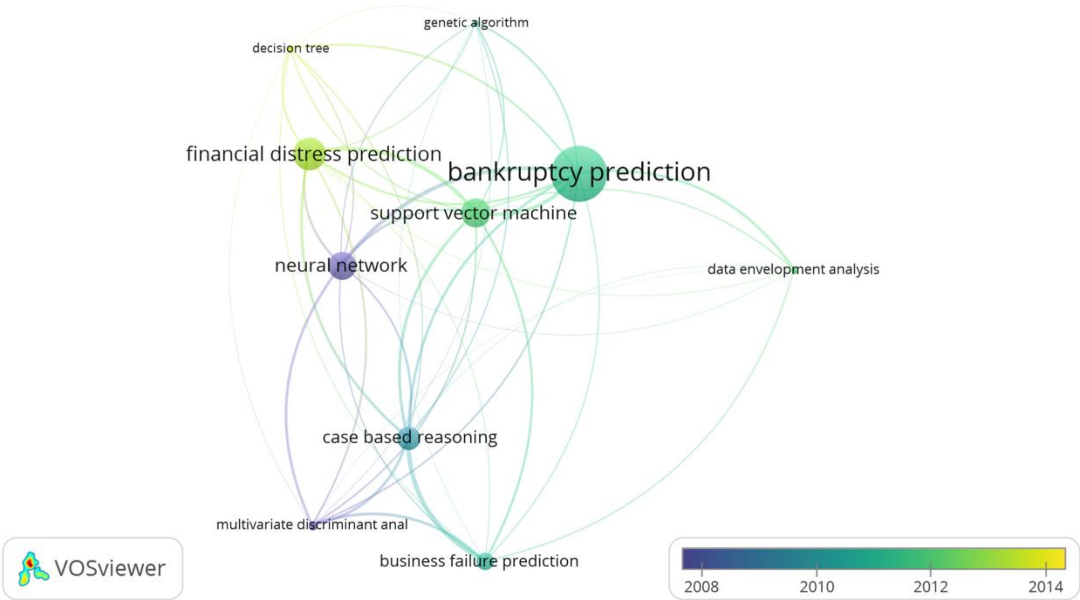
Figure 2.7: keyword co-occurrence map



2.4.7. Text mining analysis

In order to better understand the over-explored and under-explored research areas, the authors use the text mining functionality of VOSviewer as it can provide support for creating term maps based on a corpus of documents. A term map is a two-dimensional map in which terms are located in such a way that the distance between two terms can be interpreted as an indication of the relatedness of the terms (Van Eck and Waltman 2019). In this case, an overlay visualization term map has been created, based on terms extracted from a title and abstract of a corpus of academic publications in the field of intelligent techniques applied for bankruptcy prediction (see Figure 8). A full counting method has been chosen and the minimum number of occurrences of a term is configured to 50. Of the 7464 terms, 35 meet the threshold. After a relevance score calculation, which enables the authors to select the most relevant terms, 10 terms have remained.

Figure 2.8: Term map based on publications



In Figure 2.8, the smaller the distance between two terms, the stronger the terms are related to each other. The relatedness of terms is determined based on co-occurrence in documents. “The higher the occurrence of an item, the larger the node of the item” (Van Eck and Waltman 2019). It can be observed that prominent terms in this area include “bankruptcy prediction”, “financial distress prediction”, “support vector machine”, “neural network”, and “case-based reasoning”. The authors also noticed papers that used a neural network and multivariate discriminant analysis were published intensively before 2008. These two widely applied methods have been studied and explored over a long period of time. Since

2010, case-based reasoning has been applied much more frequently by researchers in this field, followed by a support vector machine and data envelopment analysis models, which were mainly developed after 2012. The decision tree presented in yellow reveals that scholars paid more attention to this technique since 2014.

Among the twelve artificial intelligent metrics discussed in this present study, only six of them are shown on the term map: support vector machine, neural network, case-based reasoning, data envelopment analysis, genetic algorithm, and decision tree. It should be noted that three of them display relatively low occurrence: data envelopment analysis, genetic algorithm and decision tree. That is to say, in the field of intelligent techniques applied to bankruptcy prediction, support vector machine, neural network and case-based reasoning are explored more than other methods. The rest of the methods, such as fuzzy, rough set, data mining, Adaboost, K-nearest neighbors, and Bayesian network may be under-explored and expected to be adopted more in the future.

2.5. Conclusions, limitations and future research

2.5.1. Conclusions and implications

A bibliometric study is carried out regarding the intelligent techniques used for bankruptcy prediction, with the objectives of identifying and assessing the trends of research in the area and presenting the evolution of published papers, co-authorship, geographical area (country/territory) of authors, co-citation, co-occurrence analysis and text mining. Some conclusions can be drawn.

First, since the first intelligent technique bankruptcy prediction paper was collected in Web of Science in 1991, the number of publications increased very slowly until 2008 when a significant increase can be observed during 2008-2009. Since then, the interest in the bankruptcy prediction research field has grown rapidly. This booming trend in terms of number of studies coincides with the collapse of the major economies due to the financial crisis from 2007-2008 and it marked great demand for applications in business failure prediction applying artificial intelligent or machine learning techniques so as to process large amounts of data (do Prado et al. 2016).

Second, the collaboration among authors is weak, especially at the international level. Among the most important authors of this research topic, Li and Sun (first and second most important authors with highest weight of citations, number of publications and total link strength) are closely linked to each other for collaborating together in publishing a great number of articles regarding bankruptcy prediction. However, main authors in this area barely collaborate with other groups, which reveals a high concentration in the co-authorship network connected between Li and Sun and dramatic difference in the total link strength from the rest of the authors. As for the country co-authorship, the most influential countries and regions, in terms of amount of publication, are China, USA, Taiwan, South Korea and Spain. The results indicate that geographically nearby countries tend to have a relatively higher level of collaborative and cooperative relationships in this area of study. Besides, the authors observe a diverse publication timeline among different countries. Researchers from the USA and South Korea published intensively before 2008, while scholars from Iran and France showed publication peak after 2014. China, Australia, India and other European countries demonstrate a growing tendency in publications from 2010, which aligns with the findings in the literature (Yu et al. 2010; do Prado et al. 2016) that more attention had been placed in bankruptcy prediction after the 2008 crisis.

Third, through the analysis of reference co-citation, the most frequently cited papers are Altman (1968), Ohlson (1980) and Beaver (1966). Although none of their work is based on an artificial intelligent-based approach, due to the fact that all aforementioned work are pioneer studies in the bankruptcy prediction field, the posterior authors tend to cite them in their papers with high frequency. In respect to the journal co-citation network, *Expert Systems with Applications* as a computer science and engineering journal, stood out among the rest of the journals in terms of both citations and total link strength. Relating discipline and journals, it is shown that computer science journals and management and finance journals have almost equal discipline distribution.

Fourth, the co-occurrence analysis reveals that the most frequently used keywords are: “bankruptcy prediction”, “neural networks”, “discriminant-analysis”, “financial distress prediction” and “classification”. The majority are related to the subject, except that discriminant analysis and neural network are methods, indicating the importance of these two techniques (statistical and artificial) in this field (Gissel et al. 2007).

Fifth, text mining is conducted by creating an overlay visualization term map based on publications regarding intelligent techniques applied in bankruptcy prediction. Observing the terms on the map, neural network and multivariate discriminant analysis have been studied and explored over a long period of time. Since 2010, case-based reasoning had been applied much more frequently than the support vector machine and data envelopment analysis models, which were mainly developed after 2012. The most recent studied metric is decision tree (after 2014). The rest of the methods, such as Fuzzy, Rough set, data mining, Adaboost, K-nearest neighbors, and Bayesian network, display a low occurrence, which reflects that the aforementioned metrics may be currently under-explored, and researchers can capture this niche for future studies.

The major contribution of this study is to bring new knowledge and key insights into the bibliometric trends of intelligent techniques applied in bankruptcy prediction study. Artificial intelligent techniques are now serving as important alternatives to statistical methods and demonstrate very promising results. Therefore, it is necessary to understand the trend in bankruptcy prediction studies and identify the intellectual structure aiming to discover new niches in this area for future research. Secondly, the results of this paper provide a comprehensive view of interdisciplinary research on bankruptcy modelling in finance, business management and computer science fields that have addressed this subject since 1968. This approach broadened the current understanding of bankruptcy prediction modelling, providing further insights in applying some under-explored alternative machine learning techniques. Thirdly, the study contributes to the theoretical development in this field as it can help graduate students and junior scholars to identify main research topics and discover possible opportunities within this field (Koseoglu

2016). Also, senior researchers from this area or other disciplines can have an overview of the evolution in this research area and dedicate future research efforts in under-explored niches.

The implications of this paper shed light on identifying under-explored areas of study and provide new insights into the existing gaps on which future studies should focus (Saggese et al. 2015). It suggests that some intelligent techniques in bankruptcy prediction studies are not sufficiently explored. However, such techniques may outperform when dealing with large data, which is crucial nowadays in management and decision making for corporate firms. In fact, artificial intelligence, as a research tool, is becoming more and more popular in many disciplines, and this gap encourages scholars and practitioners to consider the use of intelligent-based techniques as alternatives in their investigations and analysis for decision-making. Meanwhile, policy makers can also benefit from the accuracy and validity of applying machine learning methods to detect financial distressed firms in their reporting so as to proactively design regional or national policies for different industries accordingly.

2.5.2. Limitations and future research

Although the findings of this study can be helpful for researchers in this area, some limitations should be addressed. One limitation of bibliometric methods is that the corresponding quantitative approach does not reflect the context and the intention of why authors refer to other studies, so that bibliometric analysis cannot capture the complex nature of citing behavior thoroughly (Vogel and Guttel 2012). The second limitation lies on the restriction to one scientific database (the Web of Science). Therefore, a bibliometric review based on other databases can be carried out in future research.

The third limitation is related to keywords collection, where objective quantitative co-occurrence measures can be adopted. In concrete, future study can include an automatic process where articles are crawled based on meta keywords and a co-occurrence/LDA-topic definition list, so as to collect topic keywords from literature databases in a forward-backward search manner.

Additionally, it is also recommended that future studies can focus on the suitability of different artificial intelligence or machine learning algorithms for bankruptcy prediction and further evaluating their performance.

Moreover, greater dedication can address the observation of weak collaboration among authors, especially at the international dimension, in this research field. The issues raised are that weak authorships are due to some geographic limitations or there might be other important factors involved. In addition, the future authorship or co-authorship research in the bankruptcy prediction field may consider authors' affiliations and/or gender (Koseoglu 2016), which are not explored so far.

Notwithstanding these caveats, this bibliometric analysis provides new insights in identifying the under-explored niches within the bankruptcy prediction field and display the evolutionary pattern of the existing studies in the literature.

Chapter 3

3. BANKRUPTCY PREDICTION FOR THE EUROPEAN AVIATION INDUSTRY: AN APPLICATION OF THE ALTMAN MODEL

Overview. Aviation industry is extremely vulnerable to economic turbulence or the ongoing 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 Altman Z-score model using data on European airline bankruptcies over the period 2009–2019. The results indicate that the Z-score for private non-manufacturing companies shows satisfactory predictive power when applied on European aviation industry. This preliminary study is, to the best of our knowledge, the first application of a financial distress model to the European aviation industry—existing airline bankruptcy studies are mainly for U.S. airlines. We aim to bridge this gap and contribute to the literature by offering a unique and novel perspective on the Altman model's predictive power for the European air transport industry.

Keywords: financial distress; bankruptcy; insolvency; financial indicators; airline business, Altman Z-score

JEL Classification: G33, M21

3.1. Introduction

The European airline industry is highly fragmented (Smit 1997; IATA 2019). 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.

Since airline failure has a great impact on tourism and transportation activities, bankruptcy prediction is very important for policy makers, 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; 2016).

In this present study, we assess the predictive capacity of the Altman model as applied to European air carriers. This preliminary study is, to the best of our knowledge, the first application of the Altman model to the European airline industry (the majority of such studies focusing on the U.S.A.). We aim to bridge this gap and contribute to the literature by offering a unique and novel perspective on the Altman Z-score model's predictive power in the European air transportation industry.

The chapter is organized as follows. Section 3.2 starts with a literature review of principal bankruptcy prediction models and identifies the application of Altman Z-score model on aviation industry. Our research methodology is presented in Section 3.3. Section 3.4 gives a descriptive analysis of sample. The main research findings are discussed in Section 3.5. We finish in Section 6 with conclusions, limitations and future research.

3.2. 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 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 which was claimed to be able to correctly predict the bankruptcy of 95% of public manufacturing firms one year prior to failure (and 72% two 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. (2016) 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 two years prior to failure (Deakin 1972). Logit models are also found to achieve good performance (Dambolena and Shulman 1988), while the mixed logit model was stated to outperform the standard one (Jones and Hensher 2004).Other methods for bankruptcy prediction include: Probit (Kovacova and Kliestik 2017; Ahmadpour-Kasgari et al. 2012), Hazard Model (Eling and Jia 2018; Tudor et al. 2015; Dang 2013), Partial Least Squares (Serrano-Cinca and Gutiérrez-Nieto 2013; Ben Jabeur 2017). Artificial intelligent 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 intelligent techniques as: Support Vector Machine (Li et al. 2014; Lee et al. 2011), Decision tree (Kim and Upneja 2014; Chen 2011) and Case-Based Reasoning (Park and Han 2002; Li and Sun 2008).

In the airline industry, a review of bankruptcy prediction studies and the application of various models to U.S. 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 and 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 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 U.S. (Goodfriend et al. 2005)

Z-score, as a generic model, is widely used in predicting bankruptcy in the aviation industry (Gritta 1982; Gritta et al. 2011; Scaggs and Crawford 1986; Golaszewski and Sanders 1992; Stepanyan 2014; Chung and Szenberg 2012; Kolte et al. 2018). Gritta (1982) applied the Z-score to nine U.S. 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 successful predicted their insolvencies. Together with other authors, he published an update 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 U.S. 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 that Indian banks, shareholders and financial institutions to use it as tool for predicting potential bankruptcy.

Most studies show low Z-score values in U.S. airline industry. Analysis carried out by Scagges 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 airlines' financing structure, bringing consequently high interest payments. In fact, many U.S. air carriers can maintain operations with Z-score values lower than normal over a long period (Golaszewski and Sanders 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 U.S. airlines during the years 1982–1989 (Chung and 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 Lapre 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 U.S. airline financial distress prediction (Davalos et al. 1999; Gritta 1982; Stepanyan 2014; Alan and Lapré 2018; Lu et al. 2014; Ribbink et al. 2011). To the best of our knowledge, no similar studies 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 U.S.A. (Assaf and 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). Other studies analyse 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 and Connolly 2016) 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 applied the Z-Score model to European air carriers. Given the difficult situation that European airlines are struggling 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 Z′-score and Z′′-Score models to European airlines which went bankrupt in the 2009–2019 period, verify the predictive capacity of each, and compare model performance.

3.3.Methodology

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

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

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)
$1.23 < Z' < 2.9$ – "Grey" 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′′ Model, since Altman et al. (2016) 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 wildly applied for private and public manufacturing and non-manufacturing firms.

$$Z'' = 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05X_4$$

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

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 – "Grey" 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 and Z′′-Score to obtain more complete results by allowing their performance to be compared.

3.3.1. Sample construction

This study covers European airline companies that went bankrupt during the last ten years (2009–2019 The accounting and financial data required for applying Z-Score model were obtained from two databases., Amadeus and SABI (**S**istema de **A**nálisis de **B**alances **I**béricos / 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 three 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 2009–2019 period. After screening the availability of data from these databases, 17 bankrupt airlines were selected 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 Thomas Cook and VIM that went bankrupt due to administration or issues related to board of management rather than financial problems are also included.

We ranked the airlines according to the average operating revenue. This value ranges from 6.2 million to 3.8 billion euros. The operating age ranges from 3 years to 73 years. The complete ranking list is shown below (Table 3.1):

Table 3.1: Ranking by average operating revenue of European airlines that went bankrupt from 2009 to 2019.

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

Source: Amadeus and SABI database, elaborated by authors.

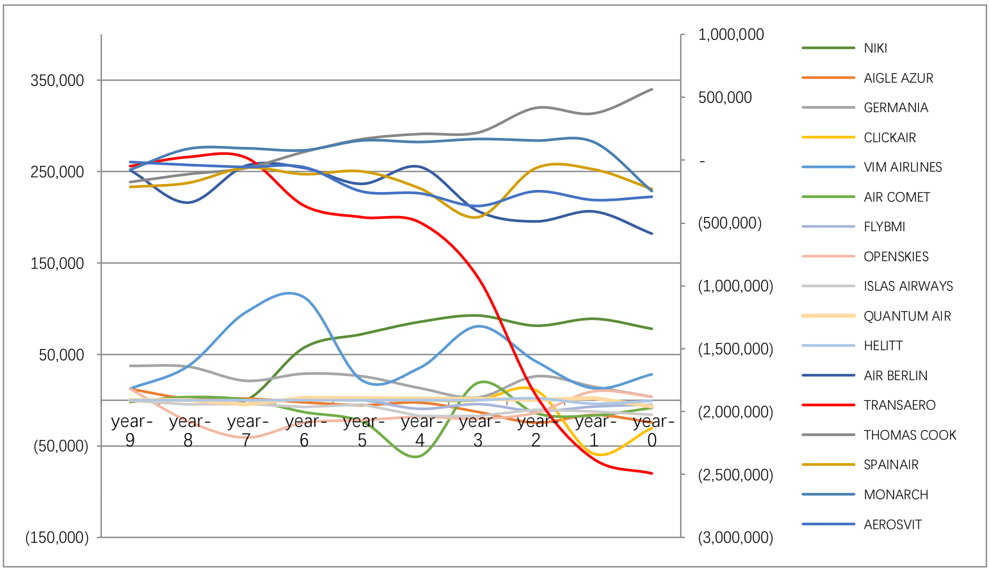
In order to better understand the main variables of the models under study, a descriptive analysis is carried out. The analysis contains changes in Working Capital, EBIT, Debt to Assets (D/A) ratio, and a global analysis of variables. In terms of liquidity measurement, Working Capital is shown to have 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 which 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 and Fernandes 2001; Guzhva and Pagiavlas 2003).

3.3.2. 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 3.1 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 five years prior to bankruptcy, and year-0 represents the last year available. Two vertical axes divide two group 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, Helitt) and while that on the right side corresponds larger ones (Air Berlin, Transaero, Thomas Cook, Spainair, Monarch, 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 as Transaero, Spainair, Air Berlin, Aerosvit had constant and declining negative working capital for the last ten years before failure. Transaero, especially, had a dramatic decline in working capital during last ten years, from 250 million euros to -2,400 million euros. Some small airlines display volatile working capital changes such as VIM airlines, Air Comet, Openskies …

Figure 3.1: Working capital changes (Euro, in '000)



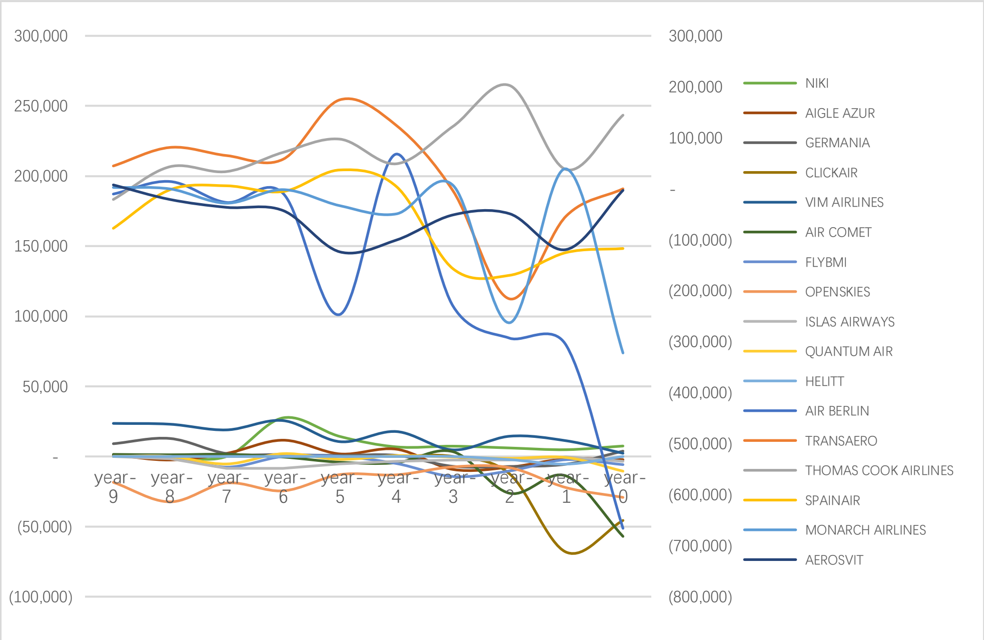
Source: Amadeus and SABI database, elaborated by authors.

3.3.3. 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 analysing the performance of a company's core operations, without considering the cost of capital structure and tax expenses.

In Figure 3.2 (as in Figure 3.1), the X axis represents the number of years before bankruptcy. Two group 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 6 larger ones (Air Berlin, …, Aerosvit Airlines). As it can be seen, many companies such as Air Berlin, Transaero, Spanair, Monarch Airlines, Air Comet, Openskies, Flybmi were all struggling with negative EBIT for years before the final failure. Air Berlin had a negative EBIT the 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 in loss for the last few years before finally going into bankruptcy.

Figure 3.2: EBIT changes (Euro, in '000)



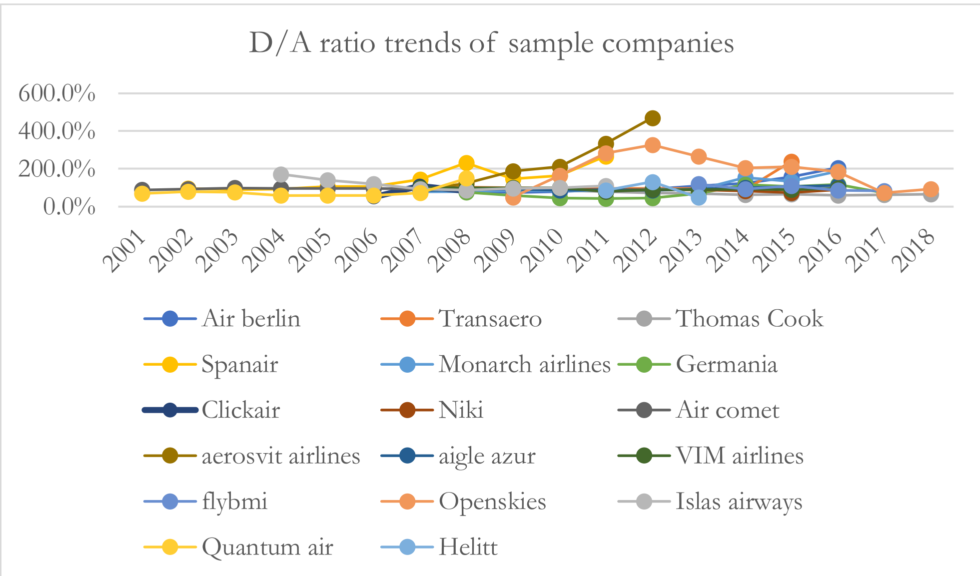
Source: Amadeus and SABI database, elaborated by authors.

3.3.4. 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 it 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 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 3.3)

Figure 3.3: Debt to Assets ratio changes for sample companies



Source: Amadeus and SABI database, elaborated by authors.

The majority of sample airlines shows D/A ratios higher than 100%. Aerosvit Airlines, Openskies and

Spanair show significantly high D/A ratios reaching 470%, 327% and 232, 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 and Fernandes 2001). Guzhva and Pagiavlas (2003) also found that U.S. airlines Pan American had increasing D/A ratio and reached 205% before it went into bankruptcy, which implies that high D/A ratio might cause insolvency before the actual bankruptcy

3.3.5 Analysis of variables

Variables included in this study are analyzed in terms of maximum value, minimum value, average value and standard deviation (see Table 3.2). X_1 = Working capital/total assets measures the liquidity. X_2 = Retained earnings/total asset is profitability ratio. X_3 = EBIT/total assets evaluate productivity of a firm. The average values of these three variables of data set are negative, indicating that the sample shows severe problem in liquidity, profitability and productivity. X_2 has the highest standard deviation: 2.5, revealing a large difference between maximum and minimum value. X_5 = sales activity of a firm. The data set show good average value of this variable, implying that although firms were bankrupted, their capital-turnover and sale generating ability were still sound

Table 3.2: Descriptive analysis of variables

		MAX	MIN	AVERAGE	ST. DE
X1	WC/TA	0.982	-11.904	-0.502	1.8
X2	RE/TA	0.976	-13.327	-0.905	2.5
X3	EBIT/TA	0.223	-4.474	-0.226	0.5
X4	EQ/TL	1.318	-0.930	0.018	0.4
X5	OR/TA	7.829	0.00003	2.195	1.5

Source: Amadeus and SABI database, elaborated by authors.

3.4. Results and discussions

We applied the Z´-score and Z´´-score models (Z´´-score emerging for emerging markets as Russia and Ukraine) on 17 selected airline companies and obtained corresponding results (see Figure 3.4). For better visualization, we classify the results into three different colour zones: “Safe” (green), “Grey” (grey) and “Distress” (red). During the analysis period (from 2001 to 2018), the time frame for each airline company ranges from three to ten years due to the available of data. For example, Quantum Air had missing data for long term debt during the year 2005–2006, therefore the corresponding results of the Z-score were not available for these two 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 and Z′′-score based on our sample. 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 grey or the distress (red) zones prior to the failure, which aligns with the results obtained by other previous studies (Gritta et al. 2011; Chung and Szenberg 2012; Stepanyan 2014; Kolte et al. 2018). Gritta et al. (2011) analysed 15 U.S. major carriers and found that the majority of airlines were within the distress zone during 1997–2006. Chung and Szenberg (2012) analysed the financial performance of seven major U.S. 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 U.S. 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 sign of insolvency up to six years prior to failure.

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

Regarding the comparison between the predictive performance of Z′ and Z′′ score, our main observations are as follows:

(a) Z′′ scores are more sensitive predictors than Z′ score. Airlines like Air Berlin, Spanair, Aigle Azur, Germania, Flybmi have Z′′ values in the distress zone but Z′ value in the grey or even safe zones. Meanwhile, airlines that have both Z′ and Z′′ value 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 grey zone while the Z′′ value in the safe zone. This reflects the fact the 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 safe zone during the last years prior to bankruptcy (Thomas Cook, Niki and VIM airlines), although Z′ score has not classified them to distress zone either, it performs slightly better than the Z′′, since the Z′ score display lower values in all these three cases.

Figure 3.4: Z´ and Z´´ results of sample companies

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

Source: Amadeus and SABI database, elaborated by authors.

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 show Z values in distress zone for at least one year prior to the declaration of bankruptcy, and unpredicted group if a firm didn't show Z value in distress zone for at least one year prior to the declaration of bankruptcy (see Table 3.3).

Table 3.3: Z´ and Z´´-score classification results

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.

Applying the Z´-score model, 11 of the17 airlines were classified in the distress zone before bankruptcy. The remaining 6 airlines show values in grey 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 (Germania, Aigle Azur, Flybmi), 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´´ value for Germania, Aigle Azur, Flybmi.

Table 3.4: Disaggregation of calculation process of Z´ and Z´´ value of Germania

$Z' = 0.717X_1 + 0.847X_2 + 3.107 X_3 + 0.420 X_4 + 0.998 X_5$						
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
$Z'' = 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05X_4$						
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.

Table 3.5: Disaggregation of calculation process of Z´ and Z´´ value of Aigle Azur

$Z' = 0.717X_1 + 0.847X_2 + 3.107 X_3 + 0.420 X_4 + 0.998 X_5$						
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
$Z'' = 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05X_4$						
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 3.6: Disaggregation of calculation process of Z´ and Z´´ value of Flybmi

$Z' = 0.717X_1 + 0.847X_2 + 3.107 X_3 + 0.420 X_4 + 0.998 X_5$						
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
$Z'' = 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05X_4$						
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.

The main finding is that, in 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 it 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 3.4), it already showed negative retained earnings, negative EBIT and negative equity four years before the bankruptcy. Z´-score didn't detect the serious situation because Germania still had good sales in 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 four years prior to bankruptcy. Aigle Azur has totally distinctive Z´ and Z´´ classification results (see Table 3.5): Z´´ scores in the danger zone for nine consecutive years before bankruptcy while Z´ score only within the grey zone. Moreover, when focusing on the four 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 (WCTA), X_2 (RETA) and X_4 (EBITTA) are negative, once one includes X_5

(ORTA), the results of Z′ score turned positive. Flymbi is similar to Aigle Azur (see Table 3.6), in that X_5 (ORTA) causes different classification results of Z′ and Z′′. While the Z′ values are mostly in grey zone, the Z′′-score, without the influences of sales, showed negative values which reveals 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 total amount) in EBIT from 2012. Afterwards, it cancelled 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.

3.5.Conclusion

We carried out an empirical study to assess the predictive capability of the Altman Z′-score and Z′′-score models on European airlines which went bankrupt during 2009–2019. This paper contributes to the existing literature as the first study of bankruptcy prediction using Z-scores on European airline data. In the descriptive analysis of our sample, we first analysed changes in Working capital, EBIT and D/A ratios. We found that the majority shows low level of Working capital and EBIT (zero or negative) before failure (from three years to ten years, depending the data availability). Regarding D/A ratios 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 comparing with other sectors, which aligns with findings of several previous studies (Gritta et al. 2011; Chung and Szenberg 2012; Stepanyan 2014; Kolte et al. 2018). 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 analysed 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 caused not primarily by financial factors, but for other reasons such as board of management and administration issues.

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 applied in the literature for U.S. airlines, the same is not true for European airlines. 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′ and Z′′-score 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, policy makers 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 level, it could help authorities to take precautionary measures to soften the negative effects that airline bankruptcies may bring to passengers, suppliers, employees and other stakeholders.

Overall, the results of our analysis are promising and suggest the viability of Z′ and Z′′-score models. As multi-country bankruptcy prediction models, they can provide useful information to predict the future financial distress of Europe airlines.

Limitation and future research

One of the major limitations is that Z-score model only takes 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. Another limitation is that of data availability, as the majority of European airlines are private firms and sampling is limited by data availability. Other databases may help in this regard.

Future research may focus on 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 analysed models have the better classification performance. Another possibility is to compare the Z-score with other standard metrics (P-score, Airscore …) in terms of bankruptcy prediction capacity. Machine learning approaches such as intelligent techniques also show promise.

Chapter 4

4. DETERMINANTS OF FINANCIAL DISTRESS IN THE EUROPEAN AIR TRANSPORT INDUSTRY: THE MODERATING EFFECT OF BEING A FLAG-CARRIER

Overview: Due to the COVID-induced global collapse in demand for air travel, the year 2020 was a catastrophic one for the aviation industry. A dramatic drop in operating revenues along with continuing fixed expenses drained the cash reserves of airlines, with consequent risks of financial distress and, potentially, even of bankruptcy. Flag-carriers are a special group in the airline business—they are considered to have privileges in terms of the support given by governments while, on the other hand, are often viewed as having low efficiency and performance. This study aims to estimate for European airlines the interaction effect of being a flag-carrier (flagship) with the relationship between leverage, liquidity, profitability, and the degree of financial distress. Findings obtained from analysing 99 European airlines over a period of ten years, indicate that the negative influence of leverage on financial stability is higher in the case of flag carriers (flagship). The impact of liquidity and profitability on financial health is more positive for flagship than for non-flagship carriers. These findings are not limited to contributing to the existing literature, but also have significant practical implications for executives, managers, and policy makers in the European air transport sector.

Keywords: financial distress; financial indicators; airline industry, Altman Z-score, flag carrier
JEL Classification: G33, M21

4.1. Introduction

COVID-19 is a highly contagious coronavirus disease and was declared a world pandemic by the WHO (World Health Organization) on March 11th, 2020. In addition to the damage, it inflicted on global health, it also caused tremendous disruption to the global economy, probably implying a long recovery period (Abate et al. 2020). Since its highly infectious nature is a major threat human society, countries have adopted response approaches such as lockdown and travel restrictions of different degrees to prevent further contagion. The most affected industries, such as tourism and air transport, have suffered massive losses (Agrawal 2020; Pongpirul 2020). The International Air Transport Association (IATA 2020) financial outlook for the global air transport industry, showed that airlines were expected to have lost $118 billion in 2020. Revenues are estimated to have halved, from $838 billion in 2019 to $419 billion in 2020.

Due to lockdown and travel restriction policies, travel demand decreased sharply, and many airlines had no choice but to reduce capacity, or even cease operation. According to IATA report (Abate et al. 2020), in this highly capital-intensive sector, airlines typically only have sufficient cash reserves to cover around two months of revenue loss. COVID-19 has had a greater influence on the airline industry than previous crises such as SARS in 2003, or the 9/11 terrorist attacks in 2001, because of their more limited geographical impact or duration time (Lange 2020; Garrow and Lurkin 2021). According to IATA, COVID-19 resulted in the most profound de-connection of modern society since World War II and, simultaneously, put aviation into a crisis (IATA 2020). Over 40 airlines were bankrupted up to October 2020, and more carriers were expected to fail in subsequent months (Abigail N. 2020). Large European flagship carriers such as Lufthansa, Air France-KLM, British Airways and Iberia had their operating activities significantly affected. Some of them took actions like reducing capacity and cutting schedules, while others suspended passenger flights for a period.

Given the scale of the loss of the airline business, around $173 billion was provided by governments to financially support the industry. This, however, had limited success. "*Some airlines received aid and averted bankruptcy, but others got no support. A few of the latter have ceased operating, and many of the remainder have severely retrenched services*" (IATA 2020). In the case of European countries, various rescue measures were employed. Some schemes were open to all airlines. For instance, the UK provided a COVID Corporate Financing Facility and Germany allowed all airlines to defer air travel taxes. In other countries, bailout aids were basically given to the national flagship carrier. Flag carrier, according to the definition given by Cambridge Dictionary, is an airline that is or was owned by a government (Cambridge 2021). It used to be an element of national identity and prestige (Windle 1991) and it showed the national capacity to operate airline of its own. National flag carriers were initially established and owned by governments and received strong protection and support from the state. Nowadays, in this era of competition and privatization, most countries are discarding the national airline model and start to commercialize their national carriers (Barrett 2006). Although most of the European flag carriers are no longer state-owned, some of them still receive more support than other non-flag carriers do. For instance, in the current COVID pandemic situation, the French and Dutch governments jointly gave €10 billion to Air France/KLM. Germany offered a €9 billion rescue deal for Lufthansa. The low-cost carrier, Ryanair, challenged the state aid given to national carriers, arguing that it was discriminatory and "*more than €30 billion in state aid had been gifted to flag carriers"* (Financial Times 2021). Although this legal challenge was rejected by the top EU court, it revealed that airlines of different types were challenged in different ways by the emergency.

Since the current pandemic has left global air carriers struggling for survival in the worst situation they have ever encountered, is has become extremely important to determine corporate financial distress risks. Financial distress can be interpreted as *"a condition where financial obligations cannot be met or being met with huge difficulties"* (Lee et al 2011; Wu et al. 2008). Financial distress prediction has been a widely researched field of study since 1960s (Beaver 1966; Altman 1968). It is vital for the management of a firm because it can affect creditors, auditors, stockholders, and senior management (Kumar and Ravi 2007). Moreover, it can provide early-warning messages on aspects that can be seen and addressed by executives and managers. To measure a firm's financial health, key financial ratios as leverage, liquidity, and profitability are most frequently considered (Altman 1968, Lee et al. 2011; Lee and Jang 2007; Zhang et al. 2020).

In the air transport industry, the Altman Z-score (one of the most famous bankruptcy-forecasting models [30]), has frequently been applied to evaluate the status of financial health and, hence, to forecast the possible financial distress of an airline [airlines (Gritta 1982; Gritta et al. 2011; Scaggs and Crawford 1986; Golaszewski and Sanders 1992; Stepanyan 2014; Chung and Szenberg 2012; Kolte et al. 2018; Agrawal 2020). It has been shown to have high predictive accuracy when applied to U.S. and Indian airlines. In 2020, Agrawal applied the Altman Z-score to estimate the influence of COVID-19 on the Indian air transport industry and it successfully reflected the difficult situation that the airlines were facing: the declining tendency of Z-scores was found, indicating higher probability of bankruptcy which can be caused by the sharp fall in passenger demand due to lockdown policies.

There is an extensive literature examining the key determinants of financial distress for various sectors of different countries (Halpern 2009; Kristanti et al. 2016; Miglani et al. 2015; Lee and Jang 2007; Kiracı 2019; Lee et al. 2011). Regarding the low-cost carrier business model in the U.S., Kiracı (2019) identified 5 ratios affecting financial distress. However, to the best of our knowledge, there is no similar study for the European airline industry, and especially none with a special focus on the moderator being a flag-carrier. In the current turbulent situation of the global aviation industry, this paper contributes to the literature by providing the first evidence, for the European air transport industry, of the flagship's moderating effect on the relationship between different financial indicators and financial health for European air transport industry. The objective of the present study is, therefore, twofold: firstly, we aim to examine the key financial ratios such as leverage, liquidity, profitability to determine if they are significantly associated to the European airline's financial distress risk. Secondly, this study seeks to explore if such influence differs when comparing flagship with non- flagship carriers.

The present chapter is organized as follow: first, a literature review was conducted on related fields of research in Section 4.2 and research hypotheses are presented. Section 4.3 introduces the methodology with sample data and models. Section 4.4 provides results of empirical analysis and discussions and, finally, conclusions, implications, limitations are presented in Section 4.5.

4.2. Literature review

4.2.1. The European airline industry

Air transport was one of the fastest growing industries (Carreras-Maide et al. 2020) offering more than 80 million jobs across the world and contributing 8% to gross domestic product. Being closely related to the international trading and tourism sector, airlines carried more than 30% of international trade and 60% of international tourist travel (Garrow and Lurkin 2021; Lange 2020). Airlines are easily affected by economic difficulties, natural disasters, and man-made disasters (Cui and Li 2017). The ongoing COVID-19 pandemic caused immense disruption to the global economy (Rababah et al. 2020) and resulted in a dramatic decrease in demand for air travel. At the worst point, April 2020, some 90% of all airline operations had ceased and, for international operations, this was closer to 98% (Garrow and Lurkin 2021; Lange 2020). In the year 2020, the global airline industry suffered a net loss of 118.5 billion dollars, undertaking only 16.4 million flights which is not even half that of the previous year (38.5 million flights). Correspondingly, half of the 87.7 million jobs that aviation was supporting before the crisis were at risk in 2020.

Europe is the one of the biggest aviation markets in the world. Since many border restrictions remain in place, the impact of the COVID-19 pandemic on air passenger numbers across Europe will continue to worsen. It is estimated that passenger numbers fell by around 60% in 2020, which represents about 705 million passenger journeys in Europe. Passenger demand recovery is predicted not to reach 2019 levels until 2024. Moreover, the revenues of the European airlines are expected to fall by more than the demand levels, since many are selling tickets with significantly discounted prices in order to stimulate air travel (IATA 2020). This sharp fall in demand and revenue led to many cases of airline bankruptcy in Europe.

Inspired by the Deregulation policy of the U.S., since the 1980s, the European Union has gradually promoted the liberalization of its air transport management system. The European trade agreement in 1992 gave more opportunities to enhance the competitive environment in European aviation (Windle 1991). This is supposed to be beneficial for consumers as it should stimulate lower prices and improved service, because this liberalization should make the market more competitive. Higher productivity and lowered unit cost should, therefore, be achieved (Windle 1991; Barros and Peypoch 2009). Flag-carriers used to benefit from special advantages in the assignment of airports, slots, ground services and large subsidies to cover their losses (Ramamurti and Sarathy 1997). To adapt the new market environment, some traditionally state-owned flag airlines, such as British Airways and Lufthansa (respectively privatized in 1987 and 1997), rebranded as successful private airlines, However, there were also flag-carriers, such as Alitalia (Italy) and Malev (Hungary), who found the transition difficult. Alitalia, the former Italian flag-carrier, is an example of state-managed failure. When it announced that it was on the verge of liquidation in 2008, to prevent it from being taken over by another country, its union still decided to reject the overall acquisition plan proposed by Air France-KLM. This despite it never having been profitable since 1999! Beria et al. (2011) reveals that Alitalia's failure was mostly caused by the interference of politicians and a network configuration designed to meet political needs more than profitability. Malev's failure, like other airlines in Greece, Poland and Portugal, shows that some European national carriers quickly turned from being shining lights to being burdens. Latterly, flying on behalf of one's country was more important than making profits. Over the years, state funding led to inefficient airline operations. Ironically, this support made it even harder for many large European airlines to survive. Early in the end of 20th century, E.U. regulators had already cancelled state subsidies for airlines, and the situation of many airlines became even worse. Windle (1991) and Ehrlich et al. (1994) found that state ownership was an explanatory factor for lower performance among European airlines, and cases of bankruptcy also indicate that *"flag-carriers were not at ease behind the national flag"*. They need to face increasing competition, including those from low-cost carriers emerged and expanded from the 1990s onwards.

4.2.2. Financial distress prediction in airline industry and the Altman Z-score

Financial distress prediction is vital for policy makers, management, and investors investors (Altman 1968; Altman et al. 2016; Ravi Kumar and Ravi 2007; Gissel et al. 2007). In fact, over the past 50 years, it has been a field of increasing interest to researchers all around the world. Altman (1968) published a pioneering paper in which he firstly used multivariate discriminant analysis approach to develop a model that was claimed to be able to correctly predict the bankruptcy of 95% of public manufacturing firms one year prior to failure (and 72% two years prior). Later in 1983, Altman introduced a re-estimated model for private firms, called Z′-score model, in 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 firms as well as service firms (Halteh et al. 2018). In 2016, he applied the Z″-score model to 31 European companies and three companies of non-European countries, and the results indicated that this model performs very satisfactorily in an international context (Altman et al. 2016). In this study, we adopted the Altman Z″-score model due to its specific characteristic for service industries (Halteh et al. 2018) and it has been widely applied as the measurement of financial risk in the U.S. aviation industry (Kiraci 2019; Davalos et al. 1999; Kroeze 2004).

In the financial distress prediction literature, statistical approaches and intelligent techniques are commonly applied for obtaining prediction models with higher accuracy. Several overview studies investigated and collected financial distress prediction models that used statistical and machine learning methods since the 1960s (Balcaen and Ooghe 2006, Ravi Kumar and Ravi 2007; Gissel et al. 2007). In the airline industry, Gritta et al. (2006) studied the application of various prediction models to U.S. air carriers. They mentioned two aviation industry specific models: the Airscore (Chow et al. 1991) and the Pilarski or P-score (Pilarski and Dinh 1999). Airscore uses an MDA approach which is similar to the Altman Z-score and the P-score also borrows three ratios from the Altman Z-score. There are, however, some deficiencies in these two models. According to one of the pioneers of the Airscore, it can be biased toward the bigger carriers in the sample (Gritta et al. 2006). Goodfriend et al. (2005) indicated that the P-score is correlated with the Altman Z-score when applied to the U.S. major carriers.

The Altman Z-score is frequently used in predicting financial distress and bankruptcy in the aviation industry (Gritta 1982; Gritta et al. 2011; Scaggs and Crawford 1986; Golaszewski and Sanders 1992; Stepanyan 2014; Chung and Szenberg 2012; Kolte et al. 2018; Agrawal 2020). It is demonstrated to be able to reflect different situations in different stage of economic cycle and it has successfully predicted insolvencies of U.S. air carriers (Gritta 1982).The application of the Z-score model in aviation industry is not limited to the U.S. airlines, Kolte et al. (2018) applied it to Indian airlines, stating that satisfactory results has been obtained and that it could be recommended as a tool for predicting potential bankruptcy to Indian banks, shareholders and financial institutions. More recently, to estimate the COVID-19 influence on the Indian airline industry, Agrawal (2020) used the Altman Z-score model and found declining scores which were assumed to be consequences of lockdown policies and the sharp fall in passenger demand. Since the Altman Z-score is considered to be one of the pioneering models for financial distress prediction, it has commonly been used in studies as a method of estimating the degree of financial distress (Kiracı 2019; Lee et al. 2011; Agrawal 2020; Venkadasalam et al. 2020).

4.2.3. Determinants of financial distress and research hypotheses

There are many studies in the literature that examine the determinants of corporate financial distress (Kiracı 2019; Lee et al. 2011; Halpern et al 2009; Kristanti et al 2016). In the aviation industry, reference Lee and Jang (2007) explored the relationship of controllable firm-specific variables and systematic risk in the U.S. airline industry. They found that debt leverage, profitability, firm size, growth, and safety were significant predictors of systematic risk. In order to find determinants of financial risk for low-cost air carriers, Kiracı (2019) collected financial data from 13 airlines that applied low-cost business model, using the Altman Z-score and the Springate S-score as indicators of financial failure (dependent variable). He found that firm leverage, assets structure, firm size, firm profitability, and liquidity affect the financial risk of airlines. Earlier, reference Lee et al (2011) used the Altman Z-score to represent a firm's degree of financial distress in order to examine the effect of capital intensity on the relationship between leverage and financial distress in U.S. restaurant industry. In their study, leverage and capital intensity were used as the main variables and firm size, profitability, growth opportunity, holdings of liquid assets and economic conditions were used as control variables. In other risk determinants studies, a variety of financial variables were chosen and empirically studied (Oliveira et al. 2017; Kristanti 2016; Miglani 2015; Zhang et al. 2020). In the present study, the adjusted Altman Z´´-score for service sector is chosen as the dependent variable to estimate a firm's financial status (higher Z values indicate better financial conditions) and three financial variables are selected from different aspects that influence the estimation of financial performance of a firm: we use leverage, liquidity, profitability and firm size, firm age and flagship as control variable. Additionally, we use flagship as moderator to see the impact it may have on the financial health of airlines.

Leverage is widely used by researchers for evaluating a firm's financial health (Lee et al 2011, Kiracı 2019; Brealey and Myers 1984; Lee and Jang 2007; Miglani et al. 2015; Kristanti et al. 2016). This ratio is frequently applied for evaluating a firm's capital structure. Previous research aimed to identify the factors that affect a firm's decision on capital structure: fixed assets, non-debt tax shields, investment opportunities, firm size, volatility, advertising expenditures, probability of bankruptcy, profitability and uniqueness of the products (Harris and Raviv 1991; Capobianco and Fernandes 2004). In general, leverage tend to increase a firm's risk (Lee et al. 2011) and high leveraged firms are believed by financial markets to be risky (Brealey and Myers 1984). In the case of the airline industry, the extreme importance of tangible assets causes airline companies to have capital-intensive and high debt dependency structures (Kiracı and Aydin 2018, Moon et al. 2015). It is normal to have a high degree of financial leverage as airlines tend to use large amounts of long-term debts to finance the purchase of assets (Gritta et al. 2006) and keep technology updated (Capobianco and Fernandez 2004).This is in line with Trade-off theory (Modigliani and Miller 1958; Myers 1984), which indicates the existence of an optimal debt to equity proportion that can be determined by the trade-off between tax advantages and disadvantages. Airlines that hold more debt will have higher tax benefit advantages, and consequently by having more tangible assets, their bankruptcy costs tend to be relatively low compared with other sectors. That explains as well why, in the air transport industry, high debt ratios are common (Kumar and Fernandez 2019; Kiracı and Aydin 2018;). This high leverage leads to greater financial risk for shareholders. In this present study, leverage is adopted as an independent variable and is measured by debt ratio (total liabilities to total assets) (Lee and Jang 2007; Kiracı 2019; Oliveira et al. 2017), and the hypotheses established for this study are:

H1a Leverage is negatively related to financial stability in European airlines.
H1b Leverage has less negative impact on the financial stability of flag carriers than of non-flag carriers.

Previous studies indicate a positive relationship between liquidity and the degree of financial health. Liquidity, as a tool for analyzing a firm's ability to pay off current debt obligations, has been commonly introduced to models in the field of financial risk determinants (Lee and Hooy 2012; Lee and Jang 2007; Kiraci 2019). It is shown as a significant determinant in many studies, but some authors may disagree. Lee and Hooy (2012) found an insignificant relationship between liquidity and systematic financial risk of airlines from North American, Europe, and Asia, which was consistent with the findings of Lee and Jang (2007) that liquidity was not significantly related to the systematic risk of the U.S. airlines. Kiraci

(2019) had obtained similar findings towards this. Considering that a firm with greater liquidity tends to use less debt and bear lower risk of financial distress, we assume that liquidity is positively related to financial health as higher liquidity ratios imply lower risk (Beaver 1970; Logue and Merville 1972; Moyer and Chartfield 1983). In our study, the liquidity ratio is measured by the current ratio, which is obtained as current assets divided by current liabilities (Lee and Jang 2007; Kiracı 2019; Stüpp 2015).

H2a Liquidity is positively related to the financial stability of European airlines.
H2b Liquidity has more positive impact on the financial stability of flag carriers than of non-flag carriers.

One of the frequently used metrics for assessing a firm's ability to generate profits and values is the profitability ratio. It normally has a positive relationship with a firm's financial health (Oliveira et al. 2017, Lee et al. 2011, Lee and Jang 2007), as high profitability can improve the ability to reduce financial instability. Also, firms with a high profitability ratio tend to have more access to external financial resources with lower interest costs (Kiracı and Aydin 2018). It is worth noting that Lee and Hooy (2012) found that profitability had significant positive effect on the systematic financial risk of North American airlines, but this effect was not significant on European and Asian airlines. Therefore, we take profitability into consideration in our model in order to see its performance as a determinant on the financial stability of European airlines. In this present study, the profitability ratio is measured by the net profit margin which is the ratio of net income to operating revenues. This ratio is widely used by relevant studies [(Winarna et al. 2017; Kim 2018; Balasubramanian et al. 2019) as it can indicate how much of each euro of revenues is left after all expenses (Apostolos G et al. 2018).

H3a Profitability is positively related to the financial stability of European airlines.
H3b Profitability has more positive impact on the financial stability of flag carriers than of non-flag carriers.

Previous research has adopted firm size and firm age for constructing risk determinants (Lee et al 2011; Kiracı 2019; Lee and Jang 2007; Oliveira et al. 2017; Halpern et al. 2009; Miglani et al. 2015; Sewpersadh 2019; Orazalin et al. 2019). There is evidence that firm size and firm age is positively related to financial health since large companies possess more recourses and old companies have more experience and consequently, are more stable under the influence of economic, social, and political changes. They tend to have better abilities to deal with financial distress issues than do small or new companies do Pindado and Rodrigues 2005; Sullivan 1978). When an airline possesses more assets or has operated for more years, it tends to have more sales and potential profits. Although it is believed to be obvious that larger and elder firms have more solid financial health, it is not yet a conclusive result since some authors have obtained different findings (Kiraci 2019; Yang and Baasandorj 2017). For instance, Kiraci 2019 found that firm size has a negative effect on financial failure score of U.S. airlines when applying Springate S-score (1978) as an indicator of financial risk. Yang and Baasandorj (2017) stated that low-cost carriers may observe significantly negative influence of firm size toward financial performance. Therefore, firm size and age are applied here as control variables which are measured by the natural logarithms of total assets and years of operation.

Flag-carriers are the main national airlines of a country the name derives from the fact that, in the past, nations' flags were painted on the aircraft in order to show the national capacity to run its own airlines. Flag carrier was considered as a symbol of the combination of entrepreneurial spirit and nationalism (Barrett 2006). Historically, although flag-carriers were owned by national governments, nowadays, government ownership is increasingly rare. Till 2004, only 5 of 18 European countries were state-owned: Air Malta (Malta), Czech Airlines (Czech Republic), Malév Hungarian Airlines (Hungary), Aegean Airlines (Greece) and TAP Air Portugal (Portugal) (Barrett 2006). However, four of them also experienced changes later. Malév Hungarian Airlines ceased operations in 2012 due to insolvency. TAP Air Portugal turned into semi-privatized in 2015, and Aegean Airlines and Czech Airlines became privately owned in 2014 and 2018, respectively. Even so, these formerly state-owned carriers still tend to be the biggest air carriers of a country and enjoy preferential rights in international operations and have advantages over other airlines. To the best of our knowledge, no previous study specifically analyses the financial status of European flag-carriers, and the current paper attempts to fill this gap.

H4: Being a flag air carrier is positively related to the financial stability of European airlines.

4.3. Methodology

4.3.1. Data sampling

In order to examine the interaction effect of flagship on the influences of key financial distress ratios in the European airline industry, the dataset for testing and analysing covers available accounting and financial data of 99 European passenger airlines during the last ten years extracted from the Amadeus database. Amadeus is a pan-European database that is commonly used for European enterprise data searching. At the time of sampling, it contained comprehensive financial information on around 21 million public and private firms across Europe (including airlines of Russia, the Ukraine and Turkey). To obtain the sample of this study, we used industry classification code 5110 (Passenger air transport). In the sample, full-service carriers, low-cost carriers, hybrid business model, regional carriers and charter airlines are included. The time frame varied for different data availability. For instance, some airlines had data available for 2019, while others only went up to 2018. Our sample includes airline data for the last available ten years.

Several requirements were established for data sampling. First, the firm should have specific accounting data for calculating the Z''-score as well as for the other ratios that are included in the model. Second, the firm should have available data for ten years in order to achieve more accurate results. After discarding companies not meeting these requirements, 990 observations remained for analysis. Of the airlines sampled, 21 are flagship. Although data for ten years is available for all sampled airlines, it is still an unbalanced panel dataset since the sampling period varies slightly by airline.

4.3.2. Variables and proposed model

Based on the literature in Sections 2.2 and 2.3, the Altman Z″-score was adopted as the dependent variable measuring the degree of financial distress adopted (Altman 1968; Altman 1983; Altman et al. 2016; Kiracı 2019; Lee et al. 2011; Agrawal 2020; Venkadasalam et al. 2020). The Altman Z″-score is an accounting-based bankruptcy prediction model, which is a modified version of the original Altman Z-score (1968) that was introduced by Altman in 1983. Altman et al. (2016) used this Z″-score model on a sample of 31 European and 3 non-European companies because these companies are mostly privately held and non-manufacturing industry. Model selection and application is consistent with Altman's 1983 proposal since (unlike the original Z-score model of 1968 for public manufacturing firms), the Z″-score is more practical when analysing airline industry because it is suitable for both public and private, manufacturing and non-manufacturing, firms. Their results suggest very satisfactory performances of Altman Z″-score model in an international context. Since the research subjects of this study contain mostly privately traded airline companies, the Altman Z″-score was chosen as the indicator of the degree of financial distress. According to the established intervals, a Z″ value less than 1.1 reveals financial distress issues. Z″ values between 1.1 and 2.6 indicate a grey zone, and firms with Z″ value greater than 2.6 are classified as having no financial difficulties. Following Altman, it is considered that higher Z″ values indicate financially healthier companies than those with lower Z″ values (Altman 1983). A firm's leverage ratio, liquidity ratio and profitability ratio are taken as independent variables. Firm size and age are used as control variable. Additionally, flagship is a dummy variable in order to examine its interaction effect. The previously mentioned variables (see Section 2.3) and the corresponding measurements, are shown as below in Table 4.1:

Table 4.1: summary of variables and measurement

	Variable name	Abbreviation	Measurement	Relevant research using corresponding variables
Dependent variable	Altman Z''-score	Z	6.56 (Working capital/Total Assets) +3.26 (Retained earnings/Total Assets) +6.72 (Earnings Before Interest and Taxation/Total Assets) +1.05 (Book Value of Equity/Book Value of Total Liabilities), and a constant coefficient of 3.25 for the firms that belong to emerging markets.	Lee et al. 2011; Kiracı 2019; Lee and Jang 2007; Orazalin et al. 2019
Main variables	Leverage ratio	LEV	Total liabilities / Total assets	Lee et al 2011; Lee and Jang 2007
	Liquidity ratio	LIQ	Current Assets / Current Liabilities	Lee and Jang 2007; Kiracı 2019; Stüpp 2015
	Net operating margin	OM	Net income/Operating revenues	Winarna et al. 2017; Kim 2018; Apostolos G et al. 2018; Balasubramanian et al. 2019
Control variables	Firm size	SIZE	Log of Total Assets	Kiracı 2019;; Oliveira et al. 2017; Halpern et al. 2009; Miglani et al. 2015
	Firm age	AGE	Log of number of years since foundation	Orazalin et al. 2019
	Flagship	FG	Flag carriers/other carriers	1=Flag air carrier, 0=Other air carriers

This study used panel data regression (Lee et al 2011; Kiracı 2019; Bezerra et al. 2019; Nguyen 2020; Pham and Doan 2020). The model employed was:

$$Z_{it} = \beta_0 + \beta_1 LEV_{it} + \beta_2 LIQ_{it} + \beta_3 OM_{it} + \beta_4 SIZE_t + \beta_5 AGE_{it} + \beta_6 FG_{it} + \beta_7 LEV{*}FG_{it} + \beta_8 LIQ{*}FG_{it} + \beta_9 OM{*}FG_{it} + \varepsilon_{it}$$

where Z represents a firm's degree of financial distress, measured by the Altman Z″-score for service sector (Altman et al. 2016). LEV represents leverage, measured by debt ratio: total liabilities to total assets. LIQ represents liquidity, measured by current assets divided by current liabilities. OM represents

Net Operating Margin, measured by net income divided by operating revenues. SIZE represents firm size, measured by log of total assets. AGE represents firm age, measured by log of number of years since foundation. FG is a dummy which takes the value of either 1 if it is a flag-carrier, or 0 if it is non-flag carrier. In this study, we used the statistical computing package R Studio software for conducting panel data analysis.

4.4. Empirical results and discussions

4.4.1. Descriptive statistics

Table 4.2 presents a descriptive analysis of the variables used in the model for 99 European airlines over the 10-year period. The mean value of Z″-score is 0.6975 with a range of -10.39 to 8.78 and standard deviation of 3.03. It should be recalled that a Z″ value less than 1.1 indicates financial distress risk and greater than 2.6 indicates the opposite. The sampled airlines show a mean Z″ value of 0.6975 which is much lower than 1.1. The median value 0.76 reveals that more than half of the sampled airlines are in an unfavourable financial condition according to this criterion. This finding is consistent with Scagges and Crawfolrd (1986), Golaszewski and Sanders (1992), Chung and Szenberg (2012) and Stepanyan (2014), that it is common for U.S. airlines to operate with low Z-scores. The leverage ratio varies from -3.19 to 4.42 with a mean of 1.2230, which implies that some of the sampled airlines have negative shareholder equity in some years. A negative debt ratio commonly indicates risk of bankruptcy since there are more liabilities than assets. Liquidity shows a mean value of 1.1366 with a range from 0.05 to 5.61, revealing a huge disparity between airlines in respect to the portion of liquid assets they possess. Regarding the operating margin, the mean value is -0.0048 with a range from -3.21 to 0.54, showing that many companies have negative EBITs in some years while others have high EBITs. The minimum age (13 years) is that of Nordwind airlines, and the maximum is for KLM (102 years). Sampled airlines has mean value of 25 years. Firm size, measured by normalization of total assets, shows a mean value of 0.0413 and a standard deviation of 0.125.

Table 4.2: Summary of Descriptive Analysis

	n	Mean	median	min	max	stdev
Z-score	990	0.6975	0.76	-10.39	8.78	3.03
Leverage	990	1.2230	1.14	-3.19	4.42	1.64
Liquidity	990	1.1366	1.01	0.05	5.61	0.68
Net operating margin	990	-0.0048	0.02	-3.21	0.54	0.19
Age (Years)	990	30.3737	25	13	102	21.42
Size (Total assets €)	990	0.0413	0.001	0.000	1	0.125

Table 4.3 shows the matrix of Pearson's correlation analysis. The dependent variable, Z″-score, shows a negative correlation with leverage ($r = -0.419$, $p < 0.001$), and a positive correlation with liquidity ($r = 0.616$, $p < 0.001$), operating margin ($r = 0.241$, $p < 0.001$), firm age ($r = 0.038$, $p = 0.23$) and firm size ($r = 0.015$, $p = 0.67$). No significant correlations were found between any of the independent variables. To check if multicollinearity existed, a Variance Inflation Factor (VIF) analysis was carried out and the results indicate that the VIF values of the variables range from 1.029 to 3.496 which are below the problematic level of 10 (Lee and Jang 2007). Hence, no severe multicollinearity is detected in the analysis.

Table 4.3: Summary of Pearson's Correlation

	Z	Leverage	Liquidity	Operating Margin	Age	Size
Z	1					
Leverage	-0.419***	1				
Liquidity	0.616***	0.119***	1			
Net operating margin	0.241***	0.189***	0.032	1		
Age	0.038	0.052*	0.018	0.049	1	
Size	0.015	0.105***	-0.113***	0.069**	0.299***	1

*** p < 0.001; ** p < 0.01; * p < 0.05

4.4.2. Empirical results

Panel regression analysis has three possible choices of regression techniques: Pooled OLS (POL), a fixed effects model (FEM), or a random effect model (REM). An F test and a Hausman test were carried out to determine which of them was most suitable for this study. The F-test result indicates that POL is not an authentic model. The Hausman test rejects the null hypothesis, suggesting that FEM is to be preferred to REM. Nevertheless, the Least Square Dummy Variable (LSDV) technique used for FEM estimation conflicts with the established dummy variable of our model. As a result, REM was chosen for conducting the regression analysis because the purpose of this study is to understand the effects of financial distress determinants in European airline industry by analysing a sample of airlines (Akbar et al. 2011)

The Breusch-Pagan test for heteroscedasticity and the Breusch-Godfrey test for serial correlation were applied to the model. The H_0 hypothesis was rejected, indicating that the model has heteroscedastic and serial correlation issues. To improve the robustness of the model by reducing possible errors in estimating the significance of coefficients, we followed the approach of Nguyen (2020) and Pham and Doan (2020) and applied Feasible Generalized Least Square (FGLS) regressions. The FGLS regression estimation results are shown in Table 4.4.

Table 4.4: summary of FGLS regression results

Step 1. Mayor effects				**Step 2. Interactions**			
	Estimate coefficient β		**Std. Error**		**Estimate coefficient β**		**Std. Error**
Intercept	-4.525	***p<0.001	-0.129	**Intercept**	-3.961	***p<0.001	0.115
LEV	-0.677	***p<0.001	-0.011	**LEV**	-0.648	***p<0.001	0.014
LIQ	3.573	***p<0.001	0.019	**LIQ**	3.562	***p<0.001	0.042
OM	3.303	***p<0.001	0.141	**OM**	2.976	***p<0.001	0.213
FG	-0.257	* p=0.046	0.079	**FG**	0.335	p=0.101	0.205
AGE	0.279	p=0.187	0.212	**AGE**	0.386	p=0.236	0.327
SIZE	1.438	* p=0.027	0.108	**SIZE**	0.939	***p<0.001	0.251
				LEV:FG	-0.046	* p=0.039	0.026
				LIQ:FG	0.358	** p=0.006	0.131
				OM:FG	10.174	***p<0.001	0.357
R^2	0.471			**R^2**	0.505		
Adj R	0.466			**Adj R**	0.497		
F	175.093			**F**	124.876		
n	990			**n**	990		

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Two stages are developed (with and without moderators) in this study in order to see more clearly the interaction effect of the model. In Step 1 we examine the mayor effects and in Step 2 we introduce the moderating term of being a flag-carrier or not. The results of the robust estimators explain significant variations in Altman Z″-scores (adjusted R^2 of 0.466 and 0.497, respectively).

In Step 1 (major effects model without interaction), a firm's leverage ratio LEV shows a negative and statistically significant effect on the Z″-score ($\beta = -0.677$, $p < 0.001$), which implies that when a firm's leverage ratio increases, the Z″-score decreases, which aggravates a firm's financial distress (Lee et al. 2011; Kiracı 2019). This result confirms our H1a hypothesis as leverage is negatively related to financial stability. It should be noted that the higher the financial failure score (Altman Z″-score) obtained, the healthier the financial status suggested for a firm, and vice versa. The other two main variables (liquidity and net profit margin) are positively related to the financial failure score, with coefficients of 3.573 and 3.303 respectively—the p values are less than 0.001, confirming H2a and H3a. Regarding the control variables, firm size shows a positive relationship with the Z″-score, indicating that large companies tend to have lower probabilities of falling into financial distress. As for the second control variable, AGE is not statistically significant in this model. Flag-carriers are more likely to have financial distress issues than other airlines, which is negatively related to the financial failure score (β=-0.257, $p <0.05$). So, Hypothesis H4 is rejected.

In the model with flagship as moderator, the regression results show that control variables AGE and FG do not have any statistically significant effect. SIZE is positively related to Z″-scores and is consistent with the results of the model without moderator. Regarding the variable LEV: FG, the results confirm that, the influence on Z″ score is negative and statistically significant (β = -0.046; $p <0.05$ for flag carriers), implying that leverage has more influence on financial stability in flag carriers and H1b is therefore rejected. A higher liquidity has a positive influence on financial health degree, higher in flag carriers (β = 0.358; $p <0.01$ for flag carriers). This result supports H2b. We also found positive and significant influence of OM: FG on Z″ score, stronger in the case of flag carriers (β = 10.174; $p <0.001$), confirming hypothesis H3b.

The obtained results confirm some of our hypotheses established for this study and reject others. A resumé of the results is shown in Table 4.5:

Table 4.5: Supported and rejected hypotheses.

Hypotheses	***Results***
H1a *Leverage is negatively related to financial stability of European airlines*	Supported
H1b *Leverage has less negative impact on financial stability of flag carriers than non-flag carriers.*	Rejected
H2a *Liquidity is positively related to financial stability of European airlines*	Supported
H2b *Liquidity has more positive impact on financial stability of flag carriers than non-flag carriers.*	Supported
H3a *Profitability is positively related to financial stability of European airlines*	Supported
H3b *Profitability has more positive impact on financial stability of flag carriers than non-flag carriers.*	Supported
H4 *Being a flag air carrier is positively related to financial stability of European airlines*	Rejected

4.4.3. Discussion

Here we consider some implications of the panel data regression results. The negative impact of leverage that we found, suggests that special attention should be paid to financial debt for controlling the financial distress risk of a company. In the aviation industry, a firm's capital structure is particularly important. Gritta (2008) indicated that, when analysing problems in the aviation industry, although a high labour cost, fuel cost spikes and overcapacity are clearly important, over-leverage at both the operating and financial levels is a deeper and more fundamental factor. A high-leveraged airline will be more vulnerable and tend to struggle with high financial interest costs and economic downturns, facing the risk of bankruptcy since they might fail to meet their obligations. Successful control of financial risk is highly dependent on how financial and operating leverages are managed (Lee and Jang 2007).

Liquidity could alleviate the degree of financial distress because more current assets can be used to prevent or lower the undesirable sales of essential assets when a firm enters a situation of financial distress (Shleifer and Vishny 1992). As for net profit margin, in order to scale up, it is essential is essential for managers and owners to increase a firm's capacity to generate profits. Besides, firms with high profitability may have a better chance of obtaining lower interest rate on debt, and consequently their financial distress risks reduce (Kiracı and Aydin 2018).

Large-sized firms tend to be more capable of absorbing the impacts of economic, social, and political change and they are more likely to become profitable due to having more resources and experience as compared to small firms. Therefore, the risk of being financially distressed reduces as firm size increases (Ben-Zion and Shalit 1975; Sullivan 1978; Pindado and Rodrigues, 2005).

It is worth noting that, the gradual privatization of flag-carriers has resulted in hardly any still being government-owned. In 1997, when the EU introduced competition into the previously protected national airlines market in order to promote efficiency through competition (Barrett 2006), Europe's previously state-backed airlines faced challenges identical those of other airlines. Although flag-carriers have passenger image advantages in that they tend to be seen as patriotic, they are still under the same pressure when operating in a deteriorating economic environment with high fuel prices. Malev from Hungary and Armavia from Armenia were flag-carriers, but they went bankrupt in 2012 and 2013, respectively. It is commonly found that, in airlines that were once state-owned, it is politically difficult to discipline managers and workers and therefore low efficiency and competitiveness arise (Ramamurti and Sarathy 2007). Alitalia, Italy's former flag carrier, had been continuously losing its competitive position since the liberalization of the European aviation market and by the year 2006, its loss had increased to 2 million euros per day (Scarpa 2007). Beria et al. (2011) argued that this essentially was because, as a flag-carrier, Alitalia was *"mainly used as a political tool rather than operating as a competitive firm"*. They stated that, although some former flag-carriers have been transformed into successful privately-owned airlines, there are others that found it difficult to adapt to the competition.

4.5. Conclusions and implications

The goal of this study is to evaluate the interaction effect of flagship on the impacts of leverage, liquidity, profitability on financial risk in the European airline industry. A sample of ten-year financial data of 99 European passenger air carriers was empirically analysed using a panel data regression method. We chose

FGLS regression for the study, and the results show outcomes that are consistent with the theoretical expectations and the established hypotheses. Firstly, the increase of the degree of debt leverage makes European airlines more vulnerable to financial distress risk, while liquidity and profitability have positive impacts on financial health. These findings are in line with the literature (Bezerra et al. 2019; Lee and Jang 2007; Lee et al. 2011; Kiracı 2019, Nguyen 2020; Turaboğlu et al. 2007). Regarding the impacts of firm size and flagship, larger carriers are less likely to fall into financial distress and flag-carriers tend to have greater financial distress risks than non-flag carriers. This study took the further step of investigating if flagship moderates the relationship between leverage, liquidity, profitability, and Z′-score. The results indicate that the negative influence of leverage on financial stability, as measured by debt ratio, is higher in the case of flag carriers. The impact of liquidity and profitability on financial health is more positive in the case of flag carriers than the non-flag ones in the European air transport market.

On the theory front, the findings of the present study enrich the literature by examining the interaction effect of flagship on the relationship between key determinants and financial distress risk in European air transport industry and separately analysing the cases of national flag-carriers and other carriers. It reflected the pressure of those former government-owned airlines that are operating in the market full of competition after liberalization.

In practical terms, the study carries significant implications for executives, managers, and policy makers in the European aviation industry—our findings can act as a reference of financial distress management when making financial strategy decisions. As a highly capital-intensive sector, the high proportion of tangible assets in the airline sector makes the cost of financial distress somewhat lower than in other industries such as IT sector. It makes executives and managers consider the use of a high-leveraged financial policy to benefit from tax deductions, as proposed by Trade-off theory. However, more attention should be paid to any early warnings of potential financial distress of the company. We find that net profit margin has a great positive influence on the financial health of a flag-carriers. Meanwhile, it plays an important role in assessing the degree of leverage, since firms with high profitability will have a higher capacity to use debt and need more benefits from tax deductions (Kiracı and Aydin 2018).

For the aviation industry, 2020 was a catastrophic year due to the collapse in demand caused by the COVID-19 pandemic. Dramatic cuts in revenues together with high fixed expenses drained airlines' cash reserves, resulting in financial distress risks (Agrawal 2020). European governments have distinctive support policies to help tide airlines over the difficulties and to avoid bankruptcy. Although countries like the UK and Germany implemented plans aimed at all airlines, other countries offered help that was limited to flag-carriers or native carriers (e.g., France and Sweden). These actions may lead to a possible regression in the liberalization process of European airline market which was undertaken to promote competitiveness and effectiveness (Financial times 2020; Ramamurti and Sarathy 2007). This unequal support may also relieve the pressure on some flag-carriers that had been trying to adapt to a higher competition market. Policy makers should take into consideration the possibility that, in the longer term, these bailout actions might set back the European air transport market.

Although the findings of the present study provide significant insights for researchers in this field of study, some limitations should be addressed. The first limitation of this study is its limited generalizability (Lee et al. 2011), the dataset used consists only of European airlines. Consequently, the findings may not generalize to airlines operating in other regions such as the U.S. and Asia. Future studies could include global data to draw more general conclusions. The second limitation arises from the selection of dependent and independent variables. To evaluate the degree of a firm's financial distress, there are many other available models in the existing literature, such as Springate S-score model (1978) and Zmijewski model (1984) that could be used as alternatives to the Altman Z-score model. In regard to the independent variables, the present model considered some specific ratios. There are, however, other ratios such as solvency and short-term debt that are commonly applied. Future research could consider adding such ratios to help in evaluating firm performance from other perspectives. Moreover, although state-owned airline is rarely to be found nowadays among the European national carriers, these national flag carriers still enjoy government aid and support, especially in a turbulent time such as COVID-19 period. Future research can analyse the political pressure and state influence on the flag carriers after receiving state aid. Furthermore, we applied flagship as the moderator and obtained significant results of interactive terms. However, state ownership, as a percentage or dummy variable, firm size, and firm age, may also be recommended as moderators to obtain results from a new perspective. Finally, it would be also interesting to explore the interactive effect of flagship or state ownership with other variable as size and operating efficiency of airlines.

Chapter 5

5. ESG DISCLOSURE IMPACT ON FINANCIAL DISTRESS IN THE AIR TRANSPORT INDUSTRY: THE MODERATING EFFECT OF BEING AN ASIA-PACIFIC AIRLINE.

Overview: The tremendous impact that COVID-19 pandemic brings to the global aviation industry has led to numerous cases of financial distress and bankruptcy of airlines. Asia-pacific region gathered more than half of the world's populations and Asia-pacific airlines makes the highest profit margin than airlines from other regions. In this study, we aim at investigating whether ESG (environmental, social and governance) practice can reduce the financial distress risk of air carriers and what this influence would be in the case of Asia-pacific region. We firstly examined the relationship between ESG disclosure and financial distress likelihood of airlines measured by Altman Z''-score. Secondly, we took a further step to analyze the moderating role of Asia-pacific airlines in such relationship. The findings supported that by improving corporate governance, airlines could mitigate the risk of financial distress, and this influence was greater in the case of Asia-pacific airlines. We sought to make contribution to the existing literature by providing empirical evidence regarding the influence of ESG on the likelihood of financial distress in airline industry. Moreover, we took the initiative to analyze the moderating role of being an Asia-pacific airline in such relationship between sustainability and financial distress. This study could bring significant implications for executives, managers, and policy makers in aviation industry regarding the ESG strategy decision and sustainability issue.

Keywords: sustainability, airline industry, environmental social and governance (ESG) score, financial distress, Altman Z-score

5.1. Introduction

Over the past fifty years, financial distress prediction has been a topic of increasing interest to researchers all around world. It is an effective approach of detecting risk and is of great importance for policymakers, management, and investors. It has been widely applied in both academic and industrial fields (Tang et al. 2020). The consequences of being financially distressed can be costly. It is estimated that when a company falls into bankruptcy, the cost of dealing with the financial distress could range from 9.5% to 16.5% of the firm value (Branch 2002). It brings also indirect cost which includes cost that refers to harmful consequences in relationship with stakeholders and leaves the company at a disadvantage when competing for gaining market share (Opler and Titman 1994; Pålsson and Beijer 2021). According to Branch (2002), once cutting off the 28% of the firm value as lost, 16% as cost of dealing with financial distress, only around 56% of the firm value could be left for claimholders. By means of receiving early-warning messages from the financial distress prediction approach, executives and managers could take precaution measures and prevent possible losses.

Financial distress prediction can be especially important during a difficult period as the ongoing COVID-19. Air transport industry, by its vulnerable nature, which is extremely easy being affected by external factors, has been significantly disrupted and suffered massive losses (Agrawal 2002, Pongpirul et al. 2020). According to the IATA (International Air Transport Association) report, the industry had a net loss of $118 billion in 2020, and revenue passenger kilometers declined 66.3% compared with 2019 (IATA 2020). Since COVID-19 exploded, up to October 2020, over 40 airlines went into bankruptcy (Abigail 2020) and more airlines are struggling for survival.

Some scholars argue that firms with a higher level of sustainability are likely to have lower downside risk and are more solid and easier to get recovered during turbulent times (Broadhstock et al. 2021, Hoepner et al. 2019). It is believed that effective corporate governance management could help to reduce or even prevent the worst aspects of the crisis (Ferrero-Ferrero et al. 2013). Evidence shows that during the 2008-2009 financial crisis, firms in the U.S. that had higher ESG (Environmental, Social, and Governance) scores showed higher financial performance than other firms (Lins et al. 2017, Cornett et al. 2016). It is suggested that a win-win situation could be achieved when a firm engaged in sustainable activities, as it could enhance its market position and obtain better long-term profits (Pålsson and Beijer 2021). Corporate sustainability activities improve a firm's competitive strength by creating opportunities to produce profits and enhance the differentiation of the company from its competitors (Miles and Covin 2000). Thus, firms with good sustainability practices are more likely to survive in turbulent situations (Mecaj and Bravo 2014). Airlines face challenges regarding sustainability because of their environmental impact and a firm with higher carbon emissions implies higher tail risk (Ilhan et al. 2020). It is crucial that airlines balance the sustainable initiatives in their business strategy, to obtain a better situation in the future.

Although the literature has keenly investigated the relationship between corporate sustainability and firm performance, it hasn't been achieved a conclusive consensus, and the literature continues to encourage researchers to explore this relationship (Kaur 2021; Pålsson and Beijer 2021). Very few studies in the literature (Al-Hadi et al. 2017; Harymawan et al. 2021; Pålsson and Beijer 2021; Kaur 2021) have focused on the impact of ESG disclosure on corporate financial distress, especially in the light of the aviation sector, so we contribute to enriching the literature by providing new insight regarding the relationship between ESG and financial distress likelihood of airlines. Some authors indicated that lack of a positive ESG orientation could have serious consequences such as loss of reputation, political and media pressure, potential fines, and penalties or even customer boycott. By increasing positive CSR activities, the probability of falling into financial distress could be decreased (Al-Hadi et al. 2017). Other authors pointed out that only Environmental and Social pillar had impact on corporate financial distress while governance pillar had no significant impact (Pålsson and Beijer 2021; Kaur 2021). Thus, we aim to ask the following research questions: What is the impact of the environmental, social and governance (ESG) scores on the likelihood of financial distress in airline industry? Is there any moderating role of being Asia pacific airline compared with other regions on this relationship between ESG and financial distress? Therefore, the objective of this research is twofold. First, we seek to examine the influence of ESG disclosure scores on the financial distress likelihood of airlines applying Altman approach. Moreover, we explore the moderating role of Asia-pacific airlines in the relationship between sustainability and financial distress risk, which is novel in this field of research. Upon both objectives, we contribute to the literature by providing empirical evidence regarding the influence of ESG on financial distress in airline industry. Furthermore, to the best of our knowledge, this is the first study taking Asia pacific airline as a moderator in the relationship between ESG and financial distress.

This paper is organized as follows: first, section 2 reviews relevant literature on the field of research and research hypotheses are presented. The methodology is introduced in section 3 with sample data, variables used, and proposed model. Section 4 provides results of empirical analysis and discussion. Finally, section 5 presents conclusions, implications, and limitations.

5.2. Literature review

5.2.1. Financial distress in airline industry and the Altman Z-score

Some literature defines financial distress as a condition that a firm fall into when it is lack of liquidity and with difficulty to meet its financial obligations (Lee et al. 2011; Wu et al. 2008; Baldwin and Scott 1983). The first signals that a financially distressed firm show are generally violations of debt covenants along with the omitted or reduced dividends (Almeida and Philippon 2007). Financial distress and ultimately bankruptcy have great negative impact on stakeholders (i.e., debtholders, customers, suppliers, and employees). It is essential for a company to predict and avoid financial distress.

The Altman Z-score was introduced by Altman in 1968 to predict the likelihood of bankruptcy (Altman 1968). It is a pioneering model using multivariate discriminant analysis approach and the original model was claimed to be able to correctly predict the bankruptcy of 95% of public manufacturing firms one year prior to failure. Later he presented a Z'-score model, in which he changed market value to the book value of equity to make the model suitable also for privately traded companies. He also provided a modified model on the basis of Z'-score, named Z"-score in which he excluded the sales/total assets ratio, stating that it could be used to predict bankruptcy for firms in service sector. Z"-score model has been applied by himself to 31 European companies and three non-European companies, and the model had very satisfactory performance in an international context (Altman et al. 2017).

Altman Z-score model has been widely applied in air transportation industry (Gritta 1982; Gritta et al. 2011; Scaggs and Crawford 1986; Golaszewski and Saunders 1992; Stepanyan 2014; Kole et al. 2018) Gritta (1982) applied Z-score model on the U.S. air carriers and stated that Z-score model is able to reflect different situations of airlines in different stage of economic cycle. The application of Z-score in airline industry is not limited to the U.S. airlines. It is recommended to Indian banks, shareholders, and financial institutions as an effective tool for predicting financial distress (Kole et al. 2018). More recently, Agrawal (2020) found declining Z scores when estimating the COVID-19 influence on the Indian aviation sector, and he assumed that it should be consequences of the lockdown policies of governments and the sharp fall in passenger demand. In this study, we adopted the modified Altman Z´´-score model due to its specific characteristic for service sectors and it has been widely applied as proxy for the risk of financial distress in the aviation industry (Kiraci 2019; Davalos et al 1999; Kroeze 2004).

5.2.2. Corporate sustainability and financial distress

Some theories regarding the corporate sustainability have been determined by previous literature of the subject, the most importance three theories including: the Stakeholder theory, the Legitimacy theory, the Resource-based view. Firstly, the stakeholder theory refers to that businesses should take into consideration every stakeholder that may be affected when company achieving objectives (Freeman and Reed 1983, Pålsson and Beijer 2021; Rivera et al. 2017). Stakeholders are reflected as all bodies involved in the business domain and is originally listed as shareowners, employees, customers, suppliers, lenders and society. (Freeman and Reed 1983). Some authors (Pålsson and Beijer 2021, Parmar et al. 2010) divided stakeholders into two groups: primary and secondary stakeholders. For a firm, primary stakeholders are vital for its existence, and secondary stakeholders don't need the firm to assume special obligations towards them, but only regular moral duties. This theory proposed that if a firm can achieve to meet the demand of its stakeholders, organizational sustainability can be reached (Abdi et al. 2021). Still, some questions arose from this perspective. The stakeholder theory could be a good measure to identify possible ethical problems, but with questioning effectiveness. Also, balancing conflicting interest problem should be faced (Orts and Strudler 2009), like if the firm benefits customers by minimizing the costs, less profits would be provided to shareholders, although both sides are stakeholders for the firm. Secondly, the legitimacy in business sustainability is interpreted by Thomas and Lamm (2012) as "the perception that organizational (strategic, structural, or procedural) changes that are proposed or implemented by organizational leaders are desirable, proper or appropriate within some socially constructed system of norm, values, or beliefs." Legitimacy theory supposes that economic issues should be considered within the political, social, and institutional framework, because society, politics and economics are inseparable (Deegan 2002). Being legitimate is important for an organization because it can improve both comprehensibility and stability of organizational activities and therefore lead to better endurance. It is due to that audiences are more willing to supply resources to organizations that seems desirable, proper or appropriate (Suchman 1995). Thirdly, the Resource-based theory focus on the necessary resources to achieve competitive advantages. The resources are understood as any assets that a firm utilize to be able to meet their goals or obtain best performance on its critical success factors (Barrutia and Echebarria 2015). This theory emphasized the crucial importance of resources for the survival, growth and overall effectiveness of the organization and managers should identify, invest in and protect such resources. In the context of corporate sustainability, corporate sustainability disclosure is believed to bring competitive advantages for the firms (Abdi et al. 2020).

Corporate sustainability and Corporate responsibility are two terms frequently used to express the sustainability in the corporate world. The concept of Corporate responsibility includes economic, social and environmental dimensions. Since 2008 global financial crisis, governance was proven to be systematic important and was added to Corporate responsibility, and the concept of ESG has emerged. Both ESG and Corporate responsibility is within the concept of Corporate sustainability. Van Marrewijk (2003) used a modified theory of Spiral Dynamics to describe five levels of Corporate sustainability: compliance-driven, profit-driven, caring, synergetic, and holistic Corporate sustainability. In this theory, the Corporate sustainability is firstly considered as a duty or a moral obligation, and then it is adopted in order to enhance financial performance and improve reputation in customers, employees or shareholders. As the level increases, corporate sustainability is no more implemented due to obligation or profit-driven reason, but conversely, that financial progress is made along with sustainable considerations. In the final level, Corporate sustainability is fully integrated in the firm's business strategy and is considered as an essential part to lengthening the firm's life (Beijer and Palsson 2021).

ESG as one dimension of Corporate sustainability has been a popular research topic (Pålsson and Beijer 2021). From the beginning of the 1970s, numerous literatures examine the impact of ESG disclosure (Friede et al. 2015), seeking for an answer to the question that if ESG is positively or negatively related to the firm performance. Some proponents and opponents are presented when discussing corporate sustainability practice. Friede et al. (2015) analyzed more than 2100 company-focused empiric studies examine the relationship between ESG reporting and corporate firm performance. The majority of the mentioned studies suggest a positive ESG relationship. However, there are opponents view arguing that ESG reporting is negatively related to financial performance. It is indicated that investment in Corporate sustainability is costly (Becchetti et al. 2008) and to achieve ESG commitment it is usually needed to sacrifice firm's financial resources (Harymawan 2021). Besides, some findings show that the benefits of ESG reporting may not be truly achieved in all cases (Revelli and Viviani 2015) and there are firms that may do not obtain payoff by investing in ESG (Harymawan 2021), or the payoff do not exceed their costs (Friedman 1970). Hence, there is no conclusive result that suggests a positive relationship between ESG reporting and corporate financial performance (Kaur 2021). Findings vary from a positive, negative and no relationship between Corporate sustainability and firm performance (Abdi et al. 2021).

While a large literature body analyzing the impact of ESG reporting on corporate financial performance, some authors sought to investigate if the financial condition affect ESG reporting. Campbell (2007) propose a theory that a firm in a weak financial status is less likely to implement corporate social responsibility (CSR) investment. It is not because it doesn't want to, but lack of sufficient capital (Harrymawan et al. 2021). A financially distressed firm is likely to be forced to implement a low-cost strategy, and the fear of losing resources reduce their willingness to achieve better performance. Reversely, other authors proposed a different point of view, that firms with high sustainability enjoy lower downside risk and are more solid during turbulent times (Broadstock et al. 2021; Hoepner et al 2019). By using ESG investment to enhance product differentiation and offer product portfolio diversification, firms can achieve to reduce systematic risk exposure. On one side, Chang et al. (2013) obtained consistent results that good ESG performance can provide insurance-like protection and enhances operational management quality, productivity, efficiency, and effectiveness in the firms during global crisis period, which contributes to decrease the probability of financial distress. On the other side, some authors indicated that the investment of ESG damages firm value (Friedman 1970). To obtain a socially responsible reputation may need a massive amount of resources that could have been allocated to other investment project, which could bring disadvantages in firm's competitiveness (Tristiarini et al 2017, Kaur 2021), and easier to fall into financially distressed.

5.2.3. ESG in airline industry

Airline is regarded as a challenging industry for implementing sustainability because of its environmental impacts and contribution to global climate change. In 2019, global flight activities produce around 915 million carbon dioxides (CO_2) releasing to the atmosphere, representing about 2% of man-made carbon emissions (Abdi et al. 2020). Environmentally sustainable initiatives for airlines includes actions like upgrading to environmentally friendly aircraft and offsetting emission footprints (Amankwah-Amoah 2020). A sustainable aviation system is proposed by ICAO that "it should be affordable, should operate safely, securely, efficiently and should offer choices of air service while supporting a competitive economy and balanced regional development." (ICAO 2013, Stevenson and Marintseva 2019).

An emerging number of literatures has been focusing on sustainability issue in airline industry (Stevenson and Martinseva 2019; Yowell (2021); Hagmann et al. 2015). Stevenson and Martinseva

(2019) conducted a review study of CSR assessment and reporting techniques in airline industry, with the conclusion that ESG can be a useful strategic focus for airlines and airports. CSR reporting practice is also analyzed by Yowell (2021) along with a sample of five airline companies. It mentioned the SASB (Sustainability Accounting standard Board) which highlighted four areas that are most notable in airline industry to disclose to their shareholders: greenhouse gas emissions, labor practices, competitive behavior and accident and safety management. He stated that the importance of CSR reporting can be observed a growing tendency for airlines, and the sampled airlines continuously provide their stakeholders with additional information of the four aspects mentioned by SASB to gain a more environmentally and socially viable image. The influence of airlines' green image is reflected on passenger choice as well, that a passenger is willing to pay extra for an airline with environmental friendliness perception (Hagmann et al. 2015).

Some authors examine the relationship between Corporate sustainability practices and airlines' firm performance or service quality, with moderating role of oil price (Lee et al. 2013), ownership (Kuo et al. 2021), firm age and size (Abdi et al. 2021) and carrier type (Seo et al. 2015). Lee et al. (2013) examines the effect of operation-related and non-operation-related CSR activities on airlines performance along with oil price as moderating role. They found that operation-related CSR has positive effect on firm performance and oil price has significant moderating effect. Kuo et al (2021) found a U-shaped relationship between ESG performance and short-term corporate financial performance (represented by ROA, Return on Assets ratio). It implies that short-term corporate performance would decline in the initial stage of implementing ESG, and after a period of time, the ROA would gradually increase. It is also shown that state-owned and private airlines experienced better short-term financial performance when implementing ESG than mixed-ownership airlines. Abdi et al. (2021) found that environmental and social initiatives would affect negatively on market-to-book ratio, but positively on firm performance represented by Tobin's q ratio. Authors interpret this as to enhance financial performance, the managers may need to expect a low market-to-book ratio for their equity. Firm size is stated to be a significant moderating role in the relationship between ESG and firm performance, but firm age is found to be insignificant. Seo et al, (2015) analyzed if CSR activities could synergistically enhance the service quality of airlines with moderating role of carrier type. They indicated that there is a positive synergistic effect of service quality and CSR for full-service carriers, and a negative synergistic effect in the case of Low-cost carrier. It suggested that implementing CSR do not always get a increased firm performance as result. An inconsistent is proposed by Yang and Baasandorj (2017). Regarding the relationship between ESG and financial performance, environmental and social performance are found to have an insignificant influence on financial performance of Low-cost carriers. Although there are many attempts to explore the relationship between ESG and firm performance in many aspects, little consistency arose from the results.

5.2.4. Asia-pacific airlines and ESG

Along with the increasing concern on airlines' sustainability implementations, studies sought to examine the sustainability practices of Asia-pacific airlines due to their specific characteristics. Asia-pacific region gathered more than half of the world's populations and airlines in this region makes the highest profit margin than airline from other regions. Some authors compared Asia-pacific airlines sustainability performance with European airlines, indicating that Asia-pacific airlines show poor CSR performance according to the DJSI (Dow Jones Sustainability Indices), which is assumed that because the concept of CSR is initially proposed in Western countries and the Asia-pacific countries are just starting to adopt the practice (Chang et al 2015). Aligning with this argument, Broadstock et al. (2019) also addressed that for example, ESG investing in China is still at an early stage of maturity. Because not like in developed markets that institutional investors have great influence on ESG investment practice, there are relatively fewer institutional investors in China and the demand of ESG products remains low. Therefore, Chinese investors are just starting to take ESG into consideration when investing. Arjomandi and Seufert (2014) evaluated technical and environmental performance of worldwide major airlines, concluding that airlines from China and North Asia are most technically efficient, but airlines from Europe have the best environmental performance. The finding of Harymawan et al. (2021) that Indonesian non-financial listed firms with low quality of ESG disclosure are likely to show financially-distress condition, raise the question that if ESG disclosure of Asia-pacific airlines could have impact on financial distress. More specifically, it is worth investigating if Asia-pacific airlines could use ESG disclosure to mitigate the risk of financial distress.

In this study, we seek for examining the relationship between ESG performance and likelihood of financial distress and the moderating role of being an Asia-pacific airline. Therefore, the following hypothesis are proposed:

H1: Corporate Environmental, Social, and Governance pillar scores have negative impact on the financial distress likelihood of airlines.

H2: Being an Asian airline moderate the effect of ESG on airlines financial distress likelihood.

5.3. Methodology

5.3.1 Data

In order to explore the relationship between financial distress likelihood and implementing sustainability activities, the dataset for testing and analyzing covers available accounting and ESG data of international passenger airlines over the period from 2011 to 2020 extracted from Thomson Reuters Eikon database. It provides the most comprehensive historical data and ESG information over 5000 globally listed companies. The Thomson Reuters ESG pillar scores aim at transparently and objectively assessing a company's sustainability performance based on reported company data (Abdi et al. 2020).

Some requirements were established for data sampling. First, the airline needs to have specific accounting and financial data for calculating the Altman Z''-score as well as for the other ratios that are used in this study. The Altman Z''-score model is chosen because it is commonly applied on companies in service sector like airlines (Kiraci 2019; Davalos et al 1999; Kroeze 2004). Second, the airline should also have available ESG data for the period of 2011-2020, same as the time frame of accounting data. After discarding airlines not meeting these requirements, 230 observations remained for the analysis of 23 airlines. Among the sampled airlines, six are from Europe, six are from North and South America, and eleven are from Asian-Pacific. The data is a balanced panel data with 23 sampled worldwide airlines (please see Appendix 1).

5.3.2. Variable and model specification

Dependent variable

In the present study, the adjusted Altman Z´´-score for service sector is chosen as the dependent variable to estimate a firm's financial distress likelihood (higher Z values indicate better financial conditions). Altman Z-score has been adopted by previous studies as measurement of financial distress risk in the field of analyzing relationship between ESG disclosure and financial distress (Kaur 2021; Pålsson and Beijer 2021). Altman used multivariate discriminant analysis approach to construct this model, and the modified Altman Z''-score for service sector is a calculation which uses coefficient and variables of the equation: 6.56 (Working capital/Total Assets) +3.26 (Retained earnings/Total Assets) +6.72 (Earnings Before Interest and Taxation/Total Assets) +1.05 (Book Value of Equity/Book Value of Total Liabilities), and a constant coefficient of 3.25 for the firms that belong to emerging markets. Kaur (2021) used Z-score as proxy for financial distress risk when evaluating the impact of financial distress on ESG performance of UK firms. Altman et al (2017) applied Z''-score model as prediction of likelihood of bankruptcy, and stated that it has very good performance especially in an international context. Since our dataset includes airlines from different continents, Altman Z''-score for service sector has been chosen as dependent variable in this study (Kiraci 2019; Davalos et al 1999; Kroeze 2004).

Main variable

The ESG pillar score offered by Thomson Reuter Eikon database is used in this study to measure the sustainability performance of airlines. The scoring process involved more than 450 measurements of corporate sustainability performance. The score values range from 0-100 and reflect corporate CSR aspects such as emissions, environmental product innovation, human rights, employment quality, training and development, community, shareholders, etc. (Duque and Aguilera 2019) It is classified into three subgroups: Environmental, Social and Governance pillars. The Environmental pillar concerns a firm's environmental responsibility. It reflects how well a firm adopt the best policies and investment to avoid environmental risk and capitalize on environmental opportunities (Abdi et al. 2021), including evaluation of resource use, emissions reductions and innovation. The Social pillar reveals a firm's commitment to the community, related with aspects like health, safety, workplace diversity, training and labor rights, employees and customer satisfaction, percentage of women employers and etc. Lastly, the Governance pillar refers to the use of good corporate governance practices (Kuo et al 2021), in order to ensure that the corporate decisions made by its members and board executives is in the best interest of its shareholders in a long term. The G score indicate a firm's strength and weakness regarding the management like board functions and structures, and CSR strategy.

Control variable

We used four control variables: leverage, liquidity, profitability, and size. These variables are identified in the previous literature when analyzing the relationship between ESG and financial distress literature (Al-Hadi et al. 2017; Harymawan et al. 2021; Pålsson and Beijer 2021; Kaur 2021). Leverage measured by total liabilities to total assets, is adopted a measurement of capital structure of a firm. According to trade-off theory, on one hand, increasing leverage can bring financial benefit to a firm, because firms can reduce income taxes by means of the tax advantages of interest expenses. On the other hand, increasing leverage could also bring cost of financial distress. In the airline industry, the extreme importance of fixed assets leads to a capital-intensive structure. Liquidity as a tool for examining a firm's ability to pay off current debt obligations, has been commonly introduced in model constructions. In this study, liquidity is measured by It has been taken into consideration of previous studies that analyzed airline industry's financial risk (Lee and Hooy 2012; Lee and Jang 2007; Kiraci 2019). Profitability is one of the commonly used metrics for analyzing a firm's ability to generate profits and values. It is often considered as positive influence on firm's financial stability. Finally, firm size is considered as the last control variable in this study. There is a conflicting argument of whether firm size has positive or negative impact on financial status of airlines (Seo et al. 2015). It is considered that operating efficiency is more accessible for larger airlines than smaller airlines (Bers and Springer 1997). But larger airlines are also more likely to suffer from operating inefficiency caused by complexity or organizational structures (Canback et al. 2006). The previously mentioned variable and the corresponding measurement are shown as below in Table 5.1:

Table 5.1: summary of variables and measurement

Variable Category	*Variable name*	*Abbreviation*	*Measurement*
Dependent variable	Altman Z"-score	Z	6.56 (Working capital/Total Assets) +3.26 (Retained earnings/Total Assets) +6.72 (Earnings Before Interest and Taxation/Total Assets) +1.05 (Book Value of Equity/Book Value of Total Liabilities), and a constant coefficient of 3.25 for the firms that belong to emerging markets.
Main variables	Environmental pillar score	ENV	Thomson Reuters score for environmental disclosure
	Social pillar score	SOC	Thomson Reuters score for social disclosure
	Governance pillar score	GOV	Thomson Reuters score for governance disclosure
Control variables	Leverage	LEV	Total liabilities to Total assets
	Liquidity	LIQ	Current Assets to Current Liabilities
	Profitability	PROF	Net income/Operating revenues
	Firm size	SIZE	Total assets
Moderating role	Asian-pacific airlines	AS	Asian-pacific airlines and non-Asian-pacific airlines.

Model specification

The present study applied panel data regression (Lee et al. 2011; Kiraci 2019; Abdi et al. 2020; Seo et al. 2015). The models employed was:

Model 1: Zit = β0 + β1ENVit + β2SOCit + β3GOVit + β4LEVt + β5LIQit + β6PROF it+ β7 SIZEit + εit

Model 2: Zit = β0 + β1ENVit + β2SOCit + β3GOVit + β4LEVt + β5LIQit + β6PROF it+ β7 SIZEit + β8 ENV*ASit + β9 SOC*ASit + β10 GOV*ASit +εit

Where Z represents the degree of financial distress, measured by the modified Z"-score for service sector

(Altman et al. 2016). ENV represents the Environmental pillar score. SOC represents the Social pillar score. GOV represents the Governance pillar score. LEV represents leverage ratio, measured by debt ratio: total liabilities to total assets. LIQ represents the liquidity ratio, measured by current assets divided by current liabilities. PROF represents net operating margin, measured by net income divided by operating revenues. SIZE represents firm size, measured by total assets of last year available of a firm. AS as moderating role is a dummy variable which takes the value of either 1 if it is an Asian-pacific airline, or 0 if it is non-Asian-pacific airline. In this study, we sued the statistical computing software Stata for conducting panel data analysis.

5.4. Empirical results and discussions

5.4.1. Descriptive statistics

The results of descriptive statistics are shown in Table 5.2. The mean Z''-score of the sampled airlines is 0.26 with a range of -5.720 to 3.956, and standard deviation of 1.691. A Z''-score equal to 0.26 is relatively low, according to the interval established by Altman (2017), that Z''-score lower than 1.1 implying financial risk while higher than 2.6 indicates the opposite case. This finding is consistent with previous literature (Scagg and Crawford 1986; Golaszewski and Saunders 1992; Chung and Szenberg 2012; Stepanyan 2014), that airlines can operate with low level of Z-scores. The mean value of ENV, SOC, GOV score of the sample airlines are all above 50, and SOC score has the highest mean value of 56.348, followed by GOV score of 54.163. The ENV score has the lowest mean value of 53.353. It should be mentioned that ENV, SOC, GOV scores range from 0 to 100. It implies that among the sustainability implementations, acting in the generating trust and loyalty with its employers, customers, and society is mostly considered and weakness of initiatives regarding environmental management is demonstrated. Leverage ranges from 0.415 to 2.124 with a mean value of 0.794. Profitability shows a negative mean of -0.0381 and the smallest standard deviations. The mean value of Liquidity is 0.8 which is less than 1, implying that sampled airlines may face the risk of being unable to meet their short-term obligations. SIZE that measured by total assets of airlines is presented in million, euros.

Table 5.2: Statistic summary

VARIABLES	N	MEAN	SD	MIN	MAX
Z	230	0.260	1.691	-5.720	3.956
ENV	230	53.353	22.566	3.364	88.023
SOC	230	56.348	18.160	13.266	93.801
GOV	230	54.163	25.092	5.852	96.069
LEV	230	0.794	0.207	0.415	2.124
PROF	230	-0.0381	0.306	-2.959	0.279
LIQ	230	0.800	0.353	0.0655	2.436
SIZE (Total assets, million euros)	230	20,294	14,630	2,467	71,996

Table 5.3 presents the Pearson's correlation analysis for variables of this study. ENV (r=-0.3677), SOC (r=-0.3060) and GOV (r=-0.1495) all negatively correlate with Z''-score. The highest r-value is -0.8244 between Leverage and Z''-score. High correlation is shown between ENV and SOC (r=-0.7981). Thus, this study provides VIF (Variance Inflation Factor) values to examine the possibility of multicollinearity. The results are less than the problematic level of 10 (Lee et al. 2007). Therefore, no severe multicollinearity is found in this analysis.

Table 5.3: correlation matrix

	Z	ENV	SOC	GOV	LEV	PROF	LIQ	SIZE
Z	1							
ENV	-0.3677* 0.00000	1						
SOC	-0.3060* 0.00000	0.7981* 0.00000	1					
GOV	-0.1495* 0.0234	0.2975* 0.00000	0.1976* 0.00260	1				
LEV	-0.8244* 0.00000	0.1999* 0.00230	0.1951* 0.00300	0.0589 0.374	1			
PROF	0.5055* 0.00000	-0.103 0.118	-0.121 0.0675	-0.0214 0.747	-0.4252* 0.00000	1		
LIQ	0.6530* 0.00000	-0.3093* 0.00000	-0.2795* 0.00000	-0.0956 0.148	-0.3784* 0.00000	0.119 0.0726	1	
SIZE	-0.101 0.127	0.4638* 0.00000	0.3799* 0.00000	0.1316* 0.0462	-0.00600 0.928	0.0157 0.813	-0.2742* 0.00000	1

Table 5.4: Variance Inflation Factor

ENV	**SOC**	**GOV**	**LEV**	**LIQ**	**PROF**	**SIZE**
3.22	2.79	1.10	1.45	1.31	1.23	1.35

5.4.2. Empirical results

The present study employs a fixed-effect model since it can account for potential problems of unobserved factors when carrying out panel data analysis (Seo et al. 2015). We first conduct an F-test, and the results indicate that the fixed effects are non-zero. The null hypothesis of the LM-test by Breusch and Pagan has been rejected that there is no individual random effect. That is, between random effect (RE) and Pooled OLS, RE should be selected. When performing a panel data analysis, whether to use a fixed effect (FE) model or a RE model is a fundamental question. Since heteroscedasticity and autocorrelation are detected in this model, one disadvantage of the Hausman test is that, if the disturbance term has heteroscedasticity, RE is not fully efficient. Therefore, the Hausman test is not suitable for the cases in which heteroscedasticity exists. We decide to use an alternative solution for model selection: the clustering robust standard error since this test method is also applicable when there is heteroscedasticity (Akhter 2018). The results indicate that FE is considered to be the suitable model. Therefore, in this study, we use the PCSE (Panel-Corrected Standard Error) method to estimate. The PCSE estimate (Beck and Katz 1995; Alfadli and Rjoub 2019; Ikpesu et al. 2019) is robust to unit heteroscedasticity (Bailey and Katz 2011) and is free from autocorrelation (Ikpesu et al. 2019). It is stated that PCSE produces more accurate standard error estimates, without any loss in efficiency (Bailey and Katz 1995).

In Table 5.5, the results of the main effects of the model show that ENV and SOC have negative but statistically insignificant associations with financial distress. GOV is statistically significant at 0.1% level with coefficient value of 0.198, demonstrating that one-unit change in GOV gives 0.198 changes in the likelihood of financial distress measured by Z”-score. In other words, one unit increase in governance pillar score gives 0,198 units decrease in financial distress risk of the sampled airlines. This result supports H1 in the governance perspective. LEV is negatively related to Z”-score, implying that higher leverage leads to a less healthy financial condition. In reverse, PROF and LIQ are significantly related with Z”-score at 0.1% level, with positive coefficients 0.489 and 0.195, respectively. The firm size of the sampled airlines has positive and insignificant effects on financial distress, indicating that the size of airlines doesn’t have any immediate effect on the financial distress likelihood.

Full panel Model 2 aggregates interaction terms ENVxAS, SOCxAS, and GOVxAS to seek the moderating role of being an Asia-pacific airline in the existing relationship between sustainability initiatives and risk of financial distress. ENV in Model 2 shows inconsistent results with Model 1that a positive association is found with financial distress, but it is still an insignificant variable in this case. SOC remains negative and insignificant, but the coefficient is slightly less negative than in model 1 (from β=-0.036 to β=-0.022). GOV is positively and significantly associated with financial distress risk at a 0.1% level with a smaller estimate coefficient (from β=0.198 to β= 0.145). The ENVxAS and SOCxAS are negatively but insignificantly related to Z”-score, with coefficient of -0.028 and -0.080, respectively. GOVxAS shows positive a relationship with Z”-score and is statistically significant on a 10% confidence level (β=0.143, $p<0.1$). It implies that GOV has more influence on financial distress likelihood in Asian-pacific airlines, supporting H2.

Table 5.5: Summary of PCSE regression estimate

Model 1: Main effect panel				*Model 2: Full panel*			
Z	**Coef.**	**Std. Err.**		**Z**	**Coef.**	**Std. Err.**	
ENV	-0.010	0.044		**ENV**	0.011	0.065	
SOC	-0.036	0.041		**SOC**	-0.022	0.037	
GOV	0.198	0.035	***	**GOV**	0.145	0.036	***
SIZE	0.009	0.035		**SIZE**	0.049	0.038	
LEV	-0.450	0.064	***	**LEV**	-0.460	0.068	***
PROF	0.489	0.093	***	**PROF**	0.510	0.087	***
LIQ	0.195	0.044	***	**LIQ**	0.190	0.039	***
				ENV*AS	-0.028	0.107	
				SOC*AS	-0.080	0.108	
				GOV*AS	0.143	0.085	.
R^2=0.78				*R^2=0.79*			
Obs= 230				*Obs= 230*			
Wald chi2(8) = 445.40				*Wald chi2(20) = 434.83*			

*** p < 0.001; ** p < 0.01; * p < 0.05; . p< 0.1

5.4.3. Robustness test

Considering the impact of COVID-19 on the data of the year 2020, we perform a structural break analysis of the dataset in order to examine the possible bias (Abdi et al. 2021). We compare the regression using dataset 2011-2020 and 2011-2019 (excluding data of year 2020), and results are shown in Table 5.6 and Table 5.7.

Although some difference in coefficients can be observed, in general the results are consistent. SIZE become significant at level of 10% confidence and GOV*AS become statistically insignificant in the Model 1 using data 2011-2019. Other variables show similar yielded estimations, indicating that no severe structural difference influence in the estimation of models. It is may due to that COVID-19 emerged in December of 2019 and so far, we only have one year data (2020) affected and such impact hasn't been reflected in the results yet.

Table 5.6: Comparison of estimation results using data 2011-2019 and 2011-2020 in Model 1

Model 1: 2011-2020				*Model 1: 2011-2019*			
Z	**Coef.**	**Std. Err.**		**Z**	**Coef.**	**Std. Err.**	
ENV	-0.010	0.044		**ENV**	-0.011	0.041	
SOC	-0.036	0.041		**SOC**	-0.063	0.041	
GOV	0.198	0.035	***	**GOV**	0.187	0.041	***
SIZE	0.009	0.035		**SIZE**	0.051	0.026	•
LEV	-0.450	0.064	***	**LEV**	-0.454	0.069	***
PROF	0.489	0.093	***	**PROF**	0.650	0.167	***
LIQ	0.195	0.044	***	**LIQ**	0.152	0.044	***
R^2=0.78				*R^2=0.79*			
Obs= 230				*Obs= 207*			
Wald chi2(8) = 445.40				*Wald chi2(20) = 421.89*			

Table 5.7: Comparison of estimation results using data 2011-2019 and 2011-2020 in Model 2

Model 2: 2011-2020				*Model 2: 2011-2019*			
Z	**Coef.**	**Std. Err.**		**Z**	**Coef.**	**Std. Err.**	
ENV	0.011	0.065		**ENV**	-0.006	0.057	
SOC	-0.022	0.037		**SOC**	-0.026	0.032	
GOV	0.145	0.036	***	**GOV**	0.145	0.034	***
SIZE	0.049	0.038		**SIZE**	0.062	0.026	
LEV	-0.460	0.068	***	**LEV**	-0.502	0.072	***
PROF	0.510	0.087	***	**PROF**	0.669	0.155	***
LIQ	0.190	0.039	***	**LIQ**	0.127	0.040	***
ENV*AS	-0.028	0.107		**ENV*AS**	0.062	0.108	
SOC*AS	-0.080	0.108		**SOC*AS**	-0.192	0.122	
GOV*AS	0.143	0.085	•	**GOV*AS**	0.113	0.090	
R^2=0.78				*R^2=0.79*			
Obs= 230				*Obs= 207*			
Wald chi2(8) = 445.40				*Wald chi2(20) = 468.01*			

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p< 0.1$

5.4.4. Discussion

We first investigated the impact of environmental, social, and governance pillar scores on financial distress likelihood measured by Z''-score, and the result partially supported established hypothesis H1. Then, we examined the moderating effect of being an Asian-pacific airline in the relationship between them and we found H2 was partially supported. We found insignificant relationship between ENV and SOC and financial distress likelihood. It recalls the question that if CSR implies a potential sacrifice of profits, why do firms promote CSR? (Chetty et al. 2015) The result implies that the capacity to obtain trust and loyalty within its workforce, customer and society may not have impact on the financial distress of airlines. By implementing initiatives to reduce environmental risk such as reduction in emission and resource use don't increase or decrease the likelihood of financial distress. One of the possible reasons could be that the cost of perusing the reputation of environmental-friendly may not be compensated by profits in return. It was found that passengers' willingness to pay extra for a green image does exist, but not as much as their willingness to pay extra for amenities (Hagmann et al. 2015). Qiu et al. (2016) obtained similar results that environmental disclosures were found to be not related to firm value. Although it was suggested by some authors that ENV and SOC actions could contribute to creating shareholder value over the long term, they didn't reflect a direct and instant effect on reducing the corporate financial distress risk. There were some arguments that CSR initiatives were shown to have positive and linear impact on value performance, but not on accounting performance for airline companies (Lee and Park 2009). This could also help to explain why insignificant ENV and SOC variables were found since Z''-score is a financial distress prediction model based on accounting information of companies.

The empirical result for the GOV pillar score, which was positively related to Z''-score, implied that higher GOV score led to a higher Z''-score which stood for lower financial distress risk. It was inconsistent with the findings of Pålsson and Beijer (2021), that an insignificant relationship was stated between GOV and risk of financial distress. One possible reason that might explain the different findings obtained is that Pålsson and Beijer (2021) used a dataset including various industries and our dataset only considered the airline industry. Some corporate governance aspects such as board independence, the board size, and women directorship were stated to be able to enhance ESG voluntary disclosure (Lagasio and Cucari 2018). Board composition and CEO/board chair structure were found to be important in the relationship with corporate bankruptcy. For example, separating the positions of CEO and board chairperson and structuring the board with a majority of independent director were recommended because they could reduce the possibility for the CEO and inside directors to behave self-servingly and costly to the firm's owners. Therefore, with these governance structures, the board would better exercise their control function and consequently would reduce the risk. Reversely, without a separated board structure or having an insider-dominated board, the firm would need to face an excessive risk like firm crisis or bankruptcy caused by an inappropriate governance structure (Daily and Dalton 1994).

Being an Asia-pacific was found to moderate the relationship between governance disclosure and financial distress likelihood. It implied that by improving aspects of corporate governance, Asia-pacific airlines could get stronger influences in preventing corporate financial distress, compared with non-Asia-pacific airlines. The moderating effect of being an Asia-pacific airline in the relationship between environmental and social disclosure and financial distress likelihood was found to be insignificant. Reviewing the related literature, this finding provided a new perspective of Asia-pacific airline's sustainability. Zhang (2021) indicated that Asia-pacific airlines focused on labor-management relations and supplier assessment, and they placed special attention to the adequacy of social information in their CSR reports compared with European airlines. Our study provided a novel finding of the moderating role of Asia-pacific airlines in the relationship between corporate governance and financial distress risk which contributed to the existing literature.

After comparing the regression results using 2011-2019 data and 2011-2020 data in our robustness analysis, we haven't found significant changes in the estimation and the impact of COVID-19 hasn't been strongly reflected. We considered that data of a longer time period would be needed for capturing the structural break under the impact of the pandemic.

5.5. Conclusions and implications

This study aimed at examining the relationship between ESG disclosure and financial distress risk, as well as the moderating role of being an Asia-pacific airline in such relationship. Both established hypothesis H1 and H2 were partially supported by the empirical results in governance perspective. Our sample consisted of ten-year ESG and financial data of 23 airlines and we added value to the existing literature by providing empirical evidence through a panel data analysis. We used the PCSE method for the study, and some results were consistent with the theoretical expectation and established hypothesis while some were contradicting. Firstly, we did not obtain any evidence supporting a significant relationship between the Environmental pillar & Social pillar and financial distress likelihood. This finding was inconsistent with Pålsson and Beijer (2021), that in their study, ENV and SOC were found to be significantly associated with Z-score and therefore these two dimensions contributed to the relationship between ESG and financial distress risk. We found that the Governance pillar had positive and statistically significant effect on financial stability, which indicated that it could reduce the risk of financial distress of airlines. We also took a further step of investigating if being an Asia-pacific airline moderates the relationship between ESG and financial stability. The results indicated that the relationship between Governance management and financial stability was different for Asia-pacific airlines compared with non-Asia-pacific airlines, that positive influence of Governance was higher in the case of Asia-pacific airlines.

Theoretically, our findings enriched the literature by evaluating the relationship between ESG and financial distress in the aviation industry and the moderating role of being an Asia-pacific airline in such relationship. The topic of corporate sustainability is going through quick changes and relevant research needs to also be updated (Pålsson and Beijer 2021). The results of this study were in line with some previous literature but not with some others. It coincided with the viewpoints proposed by various studies regarding the impact of CSR initiatives on firm performance and financial stability, however, no clear consensus has been achieved yet (Lee et al 2013). Reviewing the hypothesis established, we have not found evidence supporting that environmental and social pillar score had significant impact on financial distress likelihood, but we found governance pillar had great impact and this impact was stronger in the case of Asia-pacific airlines. Asia-pacific is a region where more than half of the world's population lives. It is predicted that Asia-pacific airlines will experience the highest growth in passenger and freight traffic until 2025. The profits margin of Asia-pacific airline industry has been significantly higher than any other region since the year of 2009 (Lee et al. 2018). Such huge market size and potential raise the question of sustainability implementations in this region. This study sought to contribute to the literature regarding this issue.

In practical terms, this study can bring significant implications for executives, managers, and policymakers in the aviation industry regarding the sustainability issue----our findings can act as a reference when making ESG strategy decisions. As a highly capital-intensive and leveraged sector, airline industry is especially vulnerable to financial distress (Opler and Titman 1994). Therefore, if airline management pays more attention to aspects like improving management structure and ESG strategies, as well as maximizing shareholder benefits, the financial stability could be enhanced. Regarding ESG initiatives, the findings of our study suggest that corporate governance should be more concerned than environmental and social aspects if a firm is willing to reduce the risk of potential financial distress. As stated by Chang et al (2015), Asia-pacific airlines may need to involve more efforts to improve the CSR programs when comparing the CSR performance with Western countries. It is suggested by the findings of this study, that by improving the corporate governance, Asia-pacific airlines could achieve a greater positive effect on reducing the likelihood of financial distress.

Some limitations should be addressed as well as future research implications. The first limitation of this study is the size of sample. The dataset used consists of only 23 airlines and they are basically the biggest airlines of a country. The reason why we used a limited number of airline sample is due to the availability of ESG data upon a timeframe of 10 years. It was also mentioned in the study of Cowper-Smith and de Grosbois (2011) that in 2009, only 14 of 41 airlines had publicly available annual CSR reports. Future research may use a bigger sample size since corporate sustainability as well as the ESG disclosure is becoming crucial, and there will be more availability of data over time. The second limitation arises from the selection of variables. Besides Altman Z-score model, there are many other models to measure the degree of financial distress of a firm, such as Springate S-score model (Springate 1978), Zmijewski model (Zmijewski 1984), and Merton's distance to default model (Merton 1974). Future research may consider using other alternative models as references of financial distress. The third limitation is that the impact of COVID-19 on performance of airlines hasn't been obviously reflected yet in our model estimation. One reason can be that such structural break needs more time to be shown and future research could shed light on the evidence of the influence that the pandemic brought to the aviation industry.

CONCLUSION

Through a systematic literature review, we obtained a comprehensive overview of literature related to corporate bankruptcy prediction. We first noticed that the topic of bankruptcy prediction in the corporate world was a field of growing interest, especially after the 2008 global financial crisis. Also, we found that apart from the classic statistical methods, there was an increasing interest in innovative machine learning methods, due to the remarkable development of big data in the 21st century. A weak co-authorship has been detected, reflecting that the collaboration among the main authors of this research area was weak. They tended to work alone, or in small groups when publishing studies. These findings arouse the question that how the application of emerged bankruptcy prediction method would be, based on intelligent techniques, and if the existing literature would have more kinds of undiscovered relationships. Therefore, we conducted a bibliometric study on intelligent techniques of corporate bankruptcy prediction, to investigate the mentioned questions.

The results of the bibliometric analysis revealed the trends of research in this area. Through the analysis of co-authorship, geographical area (country/territory) of authors, co-citation, co-occurrence analysis and text mining, we found that the most frequently cited papers are Altman (1968), Ohlson (1980) and Beaver (1966). Although none of their work was based on an artificial intelligent-based approach, due to the fact that all aforementioned works were pioneer studies in the bankruptcy prediction field, the posterior authors tended to cite them in their papers with high frequency. It was also observed that neural network and multivariate discriminant analysis had been studied and explored over a long period of time. Since 2010, case-based reasoning had been applied much more frequently than the support vector machine and data envelopment analysis models, which were mainly developed after 2012. The most recent studied metric was decision tree (after 2014). The rest of the methods, such as Fuzzy, Rough set, data mining, Adaboost, K-nearest neighbors, and Bayesian network, displayed a low occurrence, which reflected that the aforementioned metrics might be currently under-explored, and researchers could capture this niche for future studies.

In the previous chapter, we identified and assessed the trend of research in the intelligent techniques used for bankruptcy prediction. We found that although intelligent techniques have been widely used in this area, it demands a massive amount of data as input. Reviewing the results of co-citation analysis, the most cited paper was Altman (1968) in which he introduced a pioneer Altman Z-score model based on Multivariate Discriminant Analysis to predict corporate bankruptcy and it still remains relevant nowadays. It has been modified several times in order to adapt to different scenarios. We applied Z'-score and Z''-score on 17 European bankrupted airlines to examine and compare the performance of these two models. We found airlines have lower Z values compared with other sectors. Moreover, the Z'-score as a model for private manufacturing companies, showed a lower predictive capacity than the Z''-score in the aviation industry. It is aligned with the characteristic of the Z''-score model, because it is a version of Z-score that is for the service sector like air transportation. Besides, as accounting information-based models, Z' and Z'' values may be not capable of detecting business bankruptcies that caused not primarily by financial factors, but for other reasons such as board of management and administration issues. These findings contributed to the literature by offering a unique and novel perspective on the Altman Z-score model's predictive power in the European air transportation industry.

After examining the performance of Altman Z''-score in European airlines, we noticed some characteristics of European aviation industry that were different from other regions like North America. The European aviation industry is highly fragmented as most members of the European Union consider that it is important to have a national air carrier. Flag-carriers are a special group in the airline business—they are considered to have privileges in terms of the support given by governments while, on the other hand, are often viewed as having low efficiency and performance. We examined the flagship as moderating role in the relationship between three key financial ratios (leverage, liquidity, and profitability) and financial distress risk measured by Z''-score model. By using panel data analysis, we found that a negative influence of leverage on financial stability was higher in the case of flag carriers (flagship). The impacts of liquidity and profitability on financial health were more positive for flagship than for non-flagship carriers. As a highly capital-intensive sector, the high proportion of tangible assets in the airline sector makes the cost of financial distress somewhat lower than in some other industries. It encourages airlines' executives and managers to consider the use of a high-leveraged financial policy to benefit from tax deductions, as proposed by Trade-off theory. However, more attention should be paid to any early warnings of potential financial distress of the company. We found that net profit margin had a great positive influence on the financial health of a flag-carriers. Meanwhile, it plays an important role in assessing the degree of leverage, since firms with high profitability will have a higher capacity to use debt and need more benefits from tax deductions.

After encountering the COVID-19 pandemic outbreak during the research, witnessing numerous cases of financial distress and bankruptcy of airlines had posed a question of whether there was any measure that was able to enhance airlines' financial stability especially during a turbulent period. ESG practices have been paid increasing attention in the business world and some scholars found ESG implementation had positive impact on firm's performance and made firms more solid in turbulent time. Therefore, we decided to investigate whether ESG disclosure could reduce the financial risk of air carriers. We took a further step to analyze the moderating role of Asia-pacific airlines in such relationship, because although Asia-pacific region gathered more than half of the world's population, Asia-pacific airlines showed lower CSR performance than airlines of Western counties. Through a panel regression analysis based on the data of 23 sampled airlines, we found that by improving corporate governance, airlines could achieve to mitigate the risk of financial distress, and such benefit was greater in the case of Asia-pacific airlines. It encouraged airlines, especially Asia-pacific airlines to improve aspects of corporate governance such as board independence, the board size, and women directorship. Improving governance was found to be able to enhance ESG performances and consequently mitigate the risk of financial distress of airline companies.

This thesis made contributions to the literature of bankruptcy prediction analysis applying on airline industry, with special attention to flag carriers in Europe and Asia-pacific airlines. Based on the results of carried systematic literature review and bibliometric analysis, Altman Z''-score model was chosen as a proxy for the risk of financial distress. The findings obtained in this thesis are new to the existing literature since it is the first study to investigate the performance of predictive accuracy of Altman Z''-score in European airlines' bankruptcy, the determinants of financial distress of European airlines with special focus on European flag air carriers, and the relationship between ESG performance and risk of financial distress of aviation sector, with specific emphasis on the case of Asia-pacific airlines.

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