

# Risk modeling in the aviation industry as a factor of sustainable development

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**Abstract.** Research by leading economists has revealed that risks in the aviation industry affect the forecasting models of regional sustainable development. The current study is devoted to the development of approaches to risk assessment on the example of European airlines. This problem has become very problematic after several recent financial crises, when airlines around the world were going through difficult times, and dozens of them had to go bankrupt, receive financial assistance from governments or find their salvation in mergers or acquisitions with larger players in the market with the support of governments. Since the beginning of the pandemic, airlines around the world have faced many more serious problems that have forced them to stop most of their passenger flights due to restrictions aimed at reducing the incidence. Unlike other financial crises, the pandemic faces the most serious problem of uncertainty, since it is difficult to predict how the virus will behave and when it will stop. This study is aimed at developing approaches that can help identify and predict possible airline risks and establish regulatory values of significant indicators for this industry in Europe.

## 1 Introduction

As defined by Kaufman systemic risk is the likelihood of an event triggering a chain of counterparty defaults (domino effect). The idea of our research is related to the fact that for systemically important banks that are actively involved in financing large infrastructure projects with state participation, it makes sense to add a focus related to a more detailed analysis of the likelihood of insolvency and bankruptcy for large borrowers, taking into account their industry specifics and risks associated with the specifics of their activities to prevent the risk of non-repayment and thereby prevent a chain reaction—a chain of defaults. Systemically important banks are the most important financial institutions for which the stability of the entire banking system depends. As bankruptcy can have serious

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consequences for both the banking system and the economy as a whole, their activities must comply with strict criteria determined by states and international financial organizations.

As of October 2021, the Russian Federation has 13 systemically important banks (for example, among banks with state participation: Sberbank, Rosselkhozbank, VTB, and other commercial banks: Tinkoff, Promsvyazbank, Alfabank). Systemically important credit institutions are required to comply with additional capital adequacy requirements, in accordance with Basel III. Thus, the Bank of Russia established a capital adequacy premium for systemic importance from January 1, 2016 at 0.15% of risk-weighted assets, with an annual increase to reach 1% (from January 1, 2020). For example, now the minimum size of the capital adequacy ratio (N1.0) of the bank is 8%. Considering the minimum requirements for the capital adequacy premium (2.5%) and the minimum systemic importance (1%), the N1.0 ratio for systemically important credit institutions should be at least 11.5%

In our opinion, focusing on large borrowers and modeling the likelihood of insolvency and bankruptcy as part of the system for monitoring and controlling systemic risks is very important for Russian banks, which, as a rule, assesses the creditworthiness of potential borrowers and monitors the financial condition of current borrowers from the point of view of general standards, criteria, and approaches to these standards. This is also becoming especially important because, on January 1, 2022, systemically important banks will have to switch to a new standard for assessing the risk of large clients designed to prevent situations where the default of a large counterparty of the bank may lead to the insolvency of other clients. Market participants, in particular, need to monitor related borrowers and assume that the risk of one client is equal to the risk of the entire group. Russian banks are already obliged to calculate the borrower concentration ratio (N6) The new N30 standard will take into account the totality of credit requirements without weighing them by risk level. It is calculated as the ratio of all credit requirements of a client or a group of related clients to the amount of the bank's main capital, not the total capital. N30 will not exceed 25% of the share capital. Banks will have to calculate the concentration ratio for all counterparties

Therefore, it is advisable to consider the following:

1) that the well-known models for assessing the likelihood of insolvency and bankruptcy may not take into account the industry specifics and therefore may not "work" not for companies in the chosen industry.

2) New factors that must be included in the model. For example, the pandemic situation opens up space for new research in the field of modeling and assessing the likelihood of bankruptcy

Our research was conducted on the example of European airline carriers to test some hypotheses and build a model to assess the likelihood of the occurrence of probability and bankruptcy. To begin with, the whole world is living in difficult times, since the COVID-19 pandemic began at the end of 2019—the beginning of 2020. This pandemic has led to more than 140 million infections and three million deaths worldwide. In the periods of exacerbation and growth of the incidence, the governments of different countries tried to fight the virus by implementing restrictions such as curfew, closure of public places such as gyms, restaurants, museums, theatres, and so on, compulsory wearing of masks, ban on gathering in large companies, etc. Borders in most countries have closed to stop the spread of the pandemic.

This caused serious problems for most businesses, the worst of which was their bankruptcy. More precisely, the world airline industry has lost \$328 billion (40% of the previous year's level) in revenues during the pandemic. The shares of airline companies have dropped dramatically, and it is unknown when their prices return to the previous level. The most serious factor in a pandemic crisis is uncertainty. It is difficult to predict when the

pandemic will stop; thus, it is unknown what can happen with the companies in the future and when they will start to obtain the same revenues as they had earlier.

Many airlines worldwide have faced financial problems related to the stopping of most flights, close burdens, and serious concerns about bankruptcy. Currently, it is uncertain when they will return to normal functioning. Thus, in reality, one of the most important problems is the need for support from the government to remain alive. For this reason, bankruptcy prediction is an important issue not only for consumers, investors, and governments, but also for creditors and the management of companies.

Thus, the goal of the current research is to develop approaches and, in particular, a bankruptcy prediction model for airline companies. The sample will consist of the great players of the European countries; which distress can lead to the problems of their economics. The originality of this research is that the existing models usually have the global character and do not consider the features of the airline industries, although it is very important nowadays as in a pandemic it is one of the most affected industry and thus it cannot be assessed along with other industries. Also, it is important to notice that there are a few models of prediction of airlines' bankruptcy, but they were developed more than 8-10 years ago, so they lost their actuality. This research will be devoted to the airlines from Europe as a lot of economists have revealed that regional factor influenced the bankruptcy prediction models, but this hypothesis will be tested in the next investigations. The main hypotheses of the current research are.

H0: the global existing model of the bankruptcy prediction of the European companies is inaccurate in the prediction of the European airlines.

H1: the existing model of bankruptcy prediction of the European airlines developed in 2012 is actual for the current reality.

H2: high probability of bankruptcy of the European airlines directly connected with the decrease of sales to total assets ratio.

So, to achieve the goal of this research several stages will be provided:

- 1) To study the main approaches of bankruptcy prediction,
- 2) To choose the companies for the analysis,
- 3) To collect data for the analysis,
- 4) To calculate necessary financial indicators,
- 5) To build several regression models of bankruptcy prediction,
- 6) To choose the best and the most predictive model,
- 7) To apply the new model to the data sample and to compare the results with the real position of the companies,
- 8) To define the normative values for all significant variables for this industry on the base of the analysis provided in the current research,
- 9) To develop the approach of bankruptcy prediction for the European airlines.

Thus, the object of this research are the European airlines, the subject – the approach to assessing the probability of bankruptcy.

During the current investigation, several methods of the analysis were applied. Firstly, the analysis of different existing international articles was provided. Secondly, the necessary information was collected on the selected airlines. Thirdly, the financial indicators for each company were calculated in the Excel program. Fourthly, a regression analysis was carried out in the Stata package of several models to identify the most significant for the enterprises of the selected industry. Fifthly, a mathematical model for assessing the financial position was formed based on the selected significant indicators. Sixthly, the normative values for airlines were calculated. Seventhly, they were compared with normative values established in the international practice. As a result, based on the findings, the most effective algorithm for assessing the probability of deterioration of the European airlines or bankruptcy was developed.

## 2 Literature review of existing models of bankruptcy prediction

### 2.1 The Concept of bankruptcy and global bankruptcy prediction models

Bankruptcy risk is one of the types of financial risks as well as market, exchange rate, credit, liquidity risk and others. Bankruptcy means the situation of insolvency when the company cannot pay for its debts and thus cannot survive among its competitors in the market. This inability can be reflected, for example, in the dismissal of employees, low productivity, and asset destruction [1]. In the global financial environment, companies' bankruptcy risk is measured by applying different models to assess the probability of a company's bankruptcy in the near future. It is necessary to get this assessment timely both to investors to make right decisions and to managers to build the correct policy, but banks and rating agencies are also interested in it [2].

In the worldwide practice a lot of methods of bankruptcy prediction have been developed. Most of these are similar to Altman's Z-score or Ohlson's default model. However, all of them have their own disadvantages and limitations, which is the reason for ongoing searches and attempts to identify which method is the most effective, and speaking about financial institutions, which can provide the most accurate assessment of the borrower's creditworthiness to minimize possible risks and losses.

The first developed models of the empirical approach were found by Beaver (1966), [3] Altman (1968), [4] and Ohlson (1980) [5], and represent three types of the most cited methods. Beaver's model implies simple calculations and comparison of companies' individual financial indicators during several periods of time to analyze their dynamics, and if it is negative and ratios decrease under the average level to assess the closeness of bankruptcy. Altman and Ohlson's models are linear and allow us to draw a conclusion about the firm (healthy or bankrupt) on the basis of financial indicators. Altman's model is known as the Z-score and is based on multiple discriminant analysis. Initially, Altman used 22 ratios in the model, from which the 5 most significant indicators were chosen. Each coefficient has its own weight, according to its influence on the probability of default and non-repayment of the debtor's obligations. The main indicator is the coefficient of default probability (Z), which can be calculated as

$$Z\text{-score} = 0,012 X1 + 0,014 X2 + 0,033 X3 + 0,006 X4 + 0,999 X5 \quad (1)$$

where:

X1 = Working capital/ Total assets,

X2=Retained Earnings/ Total assets,

X3=Earnings before interest and tax/ Total assets,

X4=Market value equity/Book value of total debt,

X5=Sales/Total assets.

This model has the predictive power of 95% for 1-year period and 82% - for 2-years period.

Afterwards, Altman's model was improved repeatedly and in 1993 it was optimized by change of the weights and the use of the book value instead the market one in X4:

$$Z2\text{-score} = 0,717 X1 + 0,847 X2 + 3,107 X3 - 0,420 X4 + 0,998 X5 \quad (2)$$

The meaning of  $Z2 > 2,9$  means the Safe zone for the company,  $1,23 < Z2 < 2,9$  – Grey zone and  $Z2 < 1,23$  – the high probability of bankruptcy (Distress zone). In 2006 Aziz and Dar provided a study in which they tried to define which model was the most popular in 89 papers in 10 countries from 1968 to 2003 and it was Altman's Z-score.

Ohlson's model is one of the most famous representatives of the logistic regression (LR) approach and it can be provided as a sigmoid function:  $f(x) = 1 / (1 + e^{-x})$  with the

binary output which can provide a conclusion if the company is closed to bankruptcy or not. This model has the predictive power 94%.

Nowadays, there is an abundance of different models, and there are disputes in the scientific literature about their relevance, efficiency, and applied field. For example, Ashraf et al. (2019) [6] consider Altman's model to be very useful in predicting bankruptcy in emerging markets. Elviani et al. (2020) [7] studied that models created by Altman, Ohlson, Zmijevski [8] and Springate are accurate in prediction of the financial distress of the Indonesian trade companies. Salehi and Pour (2016) [9] consider that traditional prediction models can only be applied to a few industries. Shonfeld et al. (2018)[10] and Slefendorfas (2016)[11] think that these models cannot be used to provide the accurate prediction of possible distress of modern companies because the independence of businesses and changing economic environment. The advantages and limitations of several existing models are listed in Table 1.

**Table 1.** Advantages and limitations of models of bankruptcy prediction.

Bankruptcy prediction models		Advantages	Limitations
Traditional	MDA (Models of discriminant analysis) (Altman 1968) [4] (Edminster 1972) [12] (Springate 1978) (Fulmer et al. 1984)	+ high accuracy + simple calculations + long-lasting usage in practice	-dependence of only linear indicators is analyzed -macroeconomic changes, company's financial position, trends of development are not considered -the most accurate assessment can be achieved only for short period (mostly, 1 year) -models usually unrelated to the company's sector and its features
	Logistic regression models (Chesser 1974) (Ohlson 1980) (Zavgren 1985) [13]	+ considering the economic environment	-similar to MDA -accuracy of these models for the period more than 1 year is lower than MDA
Alternative	Neural networks models (Inturriaga and Sanz 2015) [14] (Du Jardin 2019) [15]	+ high accuracy + considering company's specific features + possibility of usage of complex non-linear functions and broad sets of composite data	-less studied and experienced than traditional models -special computer software is needed which increases company's costs -difficulties in defining the most accurate neural network

Source: Made by the authors.

Thus, all the models have their own advantages and limitations. All traditional models are based on simple calculations of several linear indicators that reflect a company's financial results. Alaka et al. (2018) [16] state that even though MDA are less accurate than neural network models, due to more simple calculations they are more efficient than alternative models. From the point of view of Ul Hassan et al. (2017) [17], MDA studies

only the dependence of linear indicators and the probability of bankruptcy, but changes in the economic environment are much more complicated. In addition, in the scientific literature, there are many discussions on the quantity of indicators that can be used in bankruptcy models to provide the most accurate prediction. Tomczak and Rdosinski (2017) [18] conducted one of the most famous investigations after their study of 33 MDA. They conclude that the optimal number of financial indicators in bankruptcy models is three or five, and adding more of them decreases the efficiency and accuracy of the models. The same conclusion. Fedorova et al. (2016) [19] state that the most efficient models are those that can be applied to the specific industry and they can be different according to the country and the economic sector. Glezakos et al. (2010) [20] consider that logistic regression models are the most efficient as they can be adapted to the economic environment. The opinions of neural network models are rather controversial. Some economists, such as Belas et al. (2017) [21], believe that these models can provide more useful information than traditional models. In contrast, others such as Bredart (2014) [22] concluded that using these models alone decreases the accuracy of the prediction and, as a disadvantage, they point out that these models are difficult to calculate and require large databases and a lot of time to realize..

As it was noticed there are many different models of bankruptcy prediction, they all have the common or similar explanatory variables. Du Jardin (2009) [15] points out that there are 3 types of variables usually used in bankruptcy models which characterize:

- 1) Firm's financial position through the calculation of different indicators and variables which reflect firm's structure, strategy, management, etc.
- 2) Company's economic environment through indicators related to it in general (like interest rate) or to the whole industry.
- 3) Information from financial markets of their methods to evaluate the bankruptcy risk. In other words, this point is about market efficiency when the conclusion of the possible risk of company's failure can be made not only on the base of different financial coefficients but also with the help of, for example, the analysis of the stock prices as the reflection of firm's future cash flows and thus its health.

Du Jardin [15] provided the thorough research of 190 studies of different bankruptcy prediction models and pointed out the most used variables, which are shown in the Table 2.

**Table 2.** The most common variables of the existing bankruptcy models.

<b>The most used variables in bankruptcy prediction models</b>	
<b>Variables</b>	<b>Frequency of use</b>
Financial indicator (ratio)	93%
Statistical variable (variance, mean, logarithm, standard deviation, etc) calculates with financial ratios	28%
Variation variable (changes of financial ratios over different time periods)	14%
Non-financial variable (company's: long-term strategy, market share, size, etc. or its environment's features: interest rate, sector profitability, availability of loans,etc.)	13%
Market variable (ratio related to stock price or return)	6%
Financial variable (data from financial reports)	5%

Source: Du Jardin, 2009.

The most used variable in the sample of models analyzed by Du Jardin (2009) [23] is the financial ratio:93% of studies include financial indicators, nearly 53% of them are based only on this type of variable, and 78% are composed of this variable and other types. But

there is the opinion that it is important to evaluate the size of the company to analyze its ratio and compare with others. For example, Gupta (1969) [24] points out that the larger the company, the higher the profitability and liquidity ratios, and the lower the leverage and turnover ratios. Some economists, such as Horrigan (1983) considers that the size of the company is a very important financial characteristic, and it should be considered in the bankruptcy prediction model.

The other five types of variables are rarely used in models compared to financial ratios. The second type is a statistical variable. This type presents the mathematical or statistical functions of financial variables, such as logarithm, mean, and variance, to standardize the data. The calculation of the logarithm of total assets is widely used in bankruptcy prediction. Third, variable variables allow the analysis of the position of the firm in dynamics and assess the stage of its possible failure. Fourth, non-financial variables that present quantitative and qualitative indicators can broaden the field of bankruptcy prediction from only financial analysis with the assessment of a firm's management, position in the market, size, availability of funds, the current situation of the sector, etc. Fifth, market variables are used in 6% of the models, and are based on stock prices or returns. Sixth, financial variables are used in 5% of the models; they present information from financial reports such as the size of total assets, inventories, debt, and so on. They can be used alone or in the calculation of ratios.

The most common indicators in bankruptcy models, namely financial ratios, are used not because of their predictive power but because of their economic character. Moreover, this information is easy to obtain compared to market information, which is available only for publicly quoted firms. Many studies have been conducted to compare models using different types of variables. Keasey and Watson (1987) [25] conclude that models with both financial and non-financial indicators are more accurate than models that use one of these types of variables, and that models with only ratios are better than models with only non-financial indicators. Lussier (1995)[26] found that models with only qualitative variables were not competitive in prediction because they determined healthy companies with a probability of only 73% and distressed firms with a probability of 65%. Attiya (2001) points out that models with financial ratios give more accurate results than models with market variables. Pérez (2002) [27] and Pompe and Bilderbeek (2005)[28] concluded that absolute values had the more predictive power than their variations over time.

## **2.2 Review of the Approaches to Predicting Bankruptcy in the European Countries**

In this part 2 approaches to assessing the probability of bankruptcy will be considered.

The first approach was proposed by Alaminos et al. (2016) [29], who studied 440 companies (bankrupt and non-bankrupt) of different industries in Europe, Asia, and America and established that the consideration of regional factors made the most accurate model for bankruptcy prediction. In other words, they provided models for each region and one global model for all of them, and concluded that the factors that influenced the probability of distress were not the same in the different regions and that the global model could assess it less accurately than the models that were specified for the definite region.

The model for the companies in Europe, according to their research, looks like:

$$P = -1,465 + 1,852 * X1 + 2,166 * X2 - 16,299 * X3 + 0,803 * X4 + 3,468 * X5 \quad (3), \text{ where}$$

P - the probability of bankruptcy (binary variable, 1-bankrupt, 0-not bankrupt),

X1 – Working Capital/Total assets,

X2 – Retained earnings/Total assets,

X3 – EBIT/Total assets,

X4 – Sales/Total assets,

X5 – Total debt/Total assets.

This result means that higher the indicators X1, X2, X4, X5 the higher the probability of distress. The connection between X3 and P is negative. Also, Current assets/Current liabilities and Current assets/Total assets ratios were calculated but they were defined as not significant concerning the European companies.

The second approach was made by Lee and Hooy (2012) [30] who studied airline companies in Europe, Asia and Northern America from 1990 to 2010. They used 5-factors Asset-pricing model in their analysis, which implied the calculation of these indicators:

X1 - the size of total assets,

X2 – quick liquidity ratio,

X3 – return on assets,

X4 – total debt to total assets,

X5 – operational leverage (change of EBIT divided by change of Sales),

X6 – the change of EBIT (%),

X7 -operating lease costs.

Lee and Hooy (2012) [30] concluded that risk of bankruptcy of the European airlines had the positive relationship with the operational leverage, but negative one with the growth of EBIT.

It is important to notice that only 1 indicator (Total debt/Total assets) is the same in the global approach and in the method of airlines' bankruptcy prediction. This fact points out on the fact that bankruptcy prediction is a very complicated process which depends not only on the region, but also on the industry of the companies.

### **3 Materials and method: development of the approaches of bankruptcy prediction of the European airlines in a pandemic**

#### **3.1 Data and Methodology**

In the current research, eight European airline companies (six not bankrupt and two bankrupt) are analyzed. The list of companies can be seen below in Table 3. For the analysis, the global players in the airline industry were chosen in accordance with the possible strong negative effect of their bankruptcy on the economy of the region and their country. In addition, one of the main factors in the companies' selection was the availability of all necessary data. The data were taken from the analytical source «Thomson Reuters Eikon» for 5-years period from 2016 to 2020 (for bankrupt companies, until the year of bankruptcy). The choice of the period is explained by the fact that using a 10-years period can mix the assessments because of the 2015 crisis. In other words, most companies had serious financial problems in the crisis, and some closed their subsidiaries or merged with other airlines that affected their financial statements, for example, in changing debt, revenues, and other indicators, which in turn can provide false assessments of the financial position in the long-term period. Therefore, the sample consists of companies that have not received any serious structural changes that can affect their financial position. It is important to define that the COVID crisis is rather new and actual, so it has not yet caused the bankruptcy of many global players, but it has an impact on their financial instability, which can lead to bankruptcy in the future. This is why the sample consists of two bankrupt companies and their financial data before two years of bankruptcy, which occurred after the crisis of 2015, to provide parallel with the possible future of the airlines after the pandemic.

To provide the most accurate analysis of possible distress of airline companies during a pandemic, the regression model will be built using Stata. This model defines the most



significant financial indicators that can signalize the deterioration in the financial position of companies, which can lead to bankruptcy in the future.

The dependent variable of this model is binary and indicates the probability of bankruptcy (P). For already bankrupt companies, it equals 0 for not bankrupt – 1. The model represents the mathematical expressions of several financial indicators (independent variables) with their own weights. If the result will be 1 and more, it means that the dependent variable of this model will be binary and means the probability of bankruptcy (P). For already bankrupt companies it will equal 0, for not bankrupt – 1. The model will represent the mathematical expression of several financial indicators (independent variables) with their own weights. If the result is 1 or more, it means that the probability of the firm's bankruptcy is low; in other words, it is healthy. If the result is less than 1, it means that the company is not stable and has a high probability of distress.

**Table 3.** List of the Companies.

Region	Company		Year of bankruptcy
	Not bankrupt	Bankrupt	
Europe	Deutch Lufthansa	Air Berlin	2017
	Aegean Airlines	Monarch Airlines	2017
	Air France-KLM		
	Finnair		
	Ryanair		
	Norwegian air		

Source: Made by the authors.

The independent variables used in the research are divided into 3 groups.

First, there is a group of indicators from the existing global model of bankruptcy prediction in European countries, developed by Alaminos in 2016.[29] Thus, these indicators will be used to test whether the global model is significant for the definite industry, in our case, airline companies, or is more suitable for assessing every industry separately to create a model with higher predictive power that can concern the features of the industry. As the independent variables, all ratios calculated by Alaminos for analysis purposes were assigned to group X, where:

- X1 - Current assets/Current liabilities,
- X2 – Working Capital/Total assets,
- X3 – EBIT/Total assets,
- X4 – Sales/Total assets,
- X5 – Total debt/Total assets,
- X6 - Current assets/Total assets,
- X7 – Retained earnings/Total assets.

The second group of indicators, or Z-group, was taken from Lee's model specified for airline companies and chosen accordingly the availability of necessary information. They are:

- Z1 - the size of total assets,
- Z2 – quick liquidity ratio,
- Z3 – return on assets,
- Z4 – operational leverage,
- Z5 – the change of EBIT.

Finally, the third group is chosen based on the assumption that the indicators can lead to instability of the airlines but, in their terms, are not used in the previous groups. First, the two existing models do not consider turnover ratios, mainly accounts receivable and accounts payable turnover ratios (in days). These indicators can influence the probability of

distress because their high levels or increases in the deferral of repayments mean that the consumers are not able to pay for the company in time or the company cannot pay for its creditors, which means that the company has some financial problems. Second, the total equity/total assets ratio shows how well the company is provided with its own funds. Third, return on assets ratio can be useful in bankruptcy prediction as an indicator of how effectively a company uses its assets. Therefore, the proposed ratios can be collected in the Y group as follows:

- Y1 – Accounts receivables turnover,
- Y2 – Accounts payable turnover,
- Y3 – Total equity/Total assets,
- Y4 – Return on assets (ROA).

### 3.2 Descriptive Statistics

For all 8 chosen airlines 17 indicators of X, Y, Z groups have been calculated for 5-years period from 2016-2020.

The overall descriptive statistics is presented on the Fig. 1. From this table it can be noticed that the greatest standard deviations and spreads between maximum and minimum meanings are observed in variables Y1, Y2, Z1, Z3, Z4 and Z5. Probably, some of these differences can be explained by financial position of the companies (bankrupt or not) or, for example, various size of the company (for Z1) or settlement terms (for Y1, Y2), etc.

Variable	Obs	Mean	Std. Dev.	Min	Max
X1	32	.9049609	.4501604	.1746032	1.858934
X2	32	-.0795802	.2545807	-1.124153	.1676867
X3	32	-.0135852	.2174273	-.9173292	.1556255
X4	32	.8274943	.5682608	.0695652	2.865937
X5	32	.3769945	.1926466	.0313253	1.008892
X6	32	.3441918	.18434	.0316885	.6988984
X7	32	-.0112883	.4357729	-1.826949	.3299213
Y1	32	21.55732	20.45882	1.129681	111.84
Y2	32	28.68447	22.53969	3.195374	87.69
Y3	32	.1239859	.3320133	-1.062927	.4080908
Y4	32	-.0242864	.2008767	-.82	.2177686
Z1	32	17.87149	15.92057	.4416742	48.56
Z2	32	.5031625	.3592472	.0692063	1.734587
Z3	32	-1.523661	5.780311	-16.50764	7.037769
Z4	32	.2511753	3.01469	-9.413631	8.383187
Z5	32	.4890025	4.182496	-9.67509	5.401515

**Fig. 1.** Descriptive statistics of bankrupt and not bankrupt airlines. Source: Made by the authors.

To define more concisely if the great standard deviation can be explained by the financial position, the separate tables of descriptive statistics for both bankrupt and not bankrupt companies can be built.

Descriptive statistics of not bankrupt companies is presented on the Fig. 2. It can be established that, in general, the standard deviations do not change, except the small decrease of Y1 and Y2 which means that the great spreads between minimum and maximum values of the indicators often do not arise because of the state of bankruptcy.

Concerning to the already bankrupt (Fig. 3) companies, the greatest standard deviations are shown in Y1, Y2, Z3 and Z4.

Thus, it can be concluded that the descriptive statistics has only informative character and does not allow us to make any strong conclusions or predictions, but in its term, it gives us the basic and compressed understanding of the variables and their meanings.

Variable	Obs	Mean	Std. Dev.	Min	Max
X1	32	.9049609	.4501604	.1746032	1.858934
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X6	32	.3441918	.18434	.0316885	.6988984
X7	32	-.0112883	.4357729	-1.826949	.3299213
Y1	32	21.55732	20.45882	1.129681	111.84
Y2	32	28.68447	22.53969	3.195374	87.69
Y3	32	.1239859	.3320133	-1.062927	.4080908
Y4	32	-.0242864	.2008767	-.82	.2177686
Z1	32	17.87149	15.92057	.4416742	48.56
Z2	32	.5031625	.3592472	.0692063	1.734587
Z3	32	-1.523661	5.780311	-16.50764	7.037769
Z4	32	.2511753	3.01469	-9.413631	8.383187
Z5	32	.4890025	4.182496	-9.67509	5.401515

**Fig. 2.** Descriptive statistics of not bankrupt airlines. Source: Made by the authors.

Variable	Obs	Mean	Std. Dev.	Min	Max
X1	12	1.253273	.7140003	.53	2.34
X2	12	-.0126707	.3548512	-.61	.41
X3	12	-.2107956	.3468431	-.9173292	.3068531
X4	12	2.172925	.4547924	1.524658	2.920696
X5	12	.5944237	.1518782	.4381982	1.008892
X6	12	.5962406	.1403366	.3650563	.804494
X7	12	-.5502793	.6083282	-1.826949	.1013119
Y1	12	62.2825	37.02386	20.45	111.84
Y2	12	49.96417	29.74757	11.61	87.69
Y3	12	-.2761964	.4078923	-1.062927	.1517782
Y4	12	-.2381576	.2865315	-.82	.008
Z1	12	1.398615	.9882085	.4416742	2.925
Z2	12	1.230833	.7322252	.53	2.34
Z3	12	-3.019298	11.44964	-36.63273	7.037769
Z4	12	-2.874704	11.94747	-38.70929	8.383187
Z5	12	10.44352	43.9666	-15.84346	148.372

**Fig. 3.** Descriptive statistics of bankrupt airlines. Source: Made by the authors.

## 4 Results and discussion

### 4.1 Model Development

The first step is to check whether the existing global model for bankruptcy prediction in European countries (Alamino,2016)[29] can be applied to airline companies in the same region and its predictive power

First, let us check the dependence between the probability of bankruptcy from the whole X-group of indicators, which were theoretically proposed as significant indicators before providing their analysis by Alaminos et al. [29] in 2016. The results presented in Table 7 indicate that the indicators X1, X2, and X6 are not significant in this model because their p-values exceed 0,05. However, in general, the model has a rather high predictive power, as R-squared equals 0,9516, which means that the chosen indicators can explain the probability of bankruptcy by 95,16%. Nevertheless, some ratios are not significant; thus, this model cannot be accepted. Thus, H0 is accepted.

Then, let us build the model on the basis of the chosen indicators as significant in the prediction for European companies in practice, which was proved by Alaminos et al.[29]. using a regression model. Thus, a model based only on X2, X3, X4, X5, and X7 was developed. It is important to note that this model differs from the first by the exclusion of X1 and X6, which were defined as not significant in Model 1, which can lead to the creation of a better model when X2 begins to be significant. This can occur if X2 has a strong correlation with X1 or X6, which will be excluded. The results in Fig. 4 show that X2 did not become significant, and the predictive power of the model practically did not change. This model cannot be accepted because indicator X2 has no influence on bankruptcy.

Source	SS	df	MS	Number of obs	=	32
Model	1.78419634	7	.254885191	F(7, 24)	=	67.37
Residual	.090803661	24	.003783486	Prob > F	=	0.0000
				R-squared	=	0.9516
				Adj R-squared	=	0.9374
Total	1.875	31	.060483871	Root MSE	=	.06151

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
X1	.1126652	.0678187	1.66	0.110	-.0273056 .252636
X2	-.1771328	.1060126	-1.67	0.108	-.395932 .0416665
X3	.9252264	.1575752	5.87	0.000	.6000072 1.250446
X4	-.3037398	.0644656	-4.71	0.000	-.4367903 -.1706893
X5	-.5320963	.1452987	-3.66	0.001	-.8319782 -.2322145
X6	.0090386	.1856077	0.05	0.962	-.3740369 .392114
X7	-.2672189	.1270473	-2.10	0.046	-.5294317 -.0050061
_cons	1.279828	.0793339	16.13	0.000	1.116091 1.443565

Fig. 4. Model 1 on the base of X-group indicators.

Source	SS	df	MS	Number of obs	=	32
Model	1.75274786	5	.350549572	F(5, 26)	=	74.55
Residual	.122252142	26	.004702005	Prob > F	=	0.0000
				R-squared	=	0.9348
				Adj R-squared	=	0.9223
Total	1.875	31	.060483871	Root MSE	=	.06857

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
X2	-.0036139	.0606274	-0.06	0.953	-.1282353	.1210076
X3	.6930412	.148191	4.68	0.000	.3884303	.997652
X4	-.2451504	.0495262	-4.95	0.000	-.3469531	-.1433478
X5	-.3789808	.1391656	-2.72	0.011	-.6650397	-.0929219
X7	-.0959836	.1250719	-0.77	0.450	-.3530726	.1611054
_cons	1.291278	.0879648	14.68	0.000	1.110464	1.472092

**Fig. 5.** Model 2 on the base of X-group indicators.

The second step is to test the indicators of the Z-group concerning the existing bankruptcy prediction approach in European countries (Lee et Al,2012). The model with these indicators had a very low predictive power of 25,14%. The results in Fig. 6 show that only Z3 and Z5 were significant in this model, with p-value<0,05. This indicates that the period from 2016 to 2020 differs from the events that influenced the economy before 2012 because Lee's analysis was conducted from 1990 to 2012. However, this model cannot be accepted. Thus, H1 is rejected.

Source	SS	df	MS	Number of obs	=	32
Model	.471459891	5	.094291978	F(5, 26)	=	1.75
Residual	1.40354011	26	.053982312	Prob > F	=	0.1593
				R-squared	=	0.2514
				Adj R-squared	=	0.1075
Total	1.875	31	.060483871	Root MSE	=	.23234

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
Z1	.0027357	.0027504	0.99	0.329	-.0029179	.0083894
Z2	-.0740099	.1363365	-0.54	0.592	-.3542537	.2062338
Z3	-.0521124	.0258013	-2.02	0.054	-.1051477	.000923
Z4	.0724131	.0388238	1.87	0.073	-.0073903	.1522165
Z5	.0418871	.0173878	2.41	0.023	.0061459	.0776283
_cons	.8077744	.0986614	8.19	0.000	.6049729	1.010576

**Fig. 6.** Model 3 on the base of Z-group indicators.

In the third step, only the ratios of the Y-group group were tested (Table 10). The model with only these indicators has better predictive power than the Z-based model, but less than the X-based model. This model, in general, can explain 82% of bankruptcies but it cannot be accepted because the insignificance of Y1 and Y2

Source	SS	df	MS	Number of obs =	32
Model	1.53998039	4	.384995098	F(4, 27) =	31.03
Residual	.335019606	27	.012408134	Prob > F =	0.0000
				R-squared =	0.8213
				Adj R-squared =	0.7949
Total	1.875	31	.060483871	Root MSE =	.11139

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
Y1	.0004876	.0015174	0.32	0.750	-.0026258 .003601
Y2	-.000405	.0015234	-0.27	0.792	-.0035308 .0027207
Y3	.3040107	.1331465	2.28	0.031	.0308167 .5772047
Y4	.6501702	.1972988	3.30	0.003	.2453465 1.054994
_cons	.9167042	.0553485	16.56	0.000	.8031385 1.03027

**Fig. 7.** Model 3 on the base of Y-group indicators.

It can be concluded that all models are not concise enough to assess the probability of possible distress of the European airlines from 2016 to 2020, and the goal is to provide the most accurate model with the highest predictive power, with all indicators being significant. In addition, all three models considered above have problems of multicollinearity and heteroscedasticity; thus, the new model should exclude these problems. To begin with the building of the correlation matrix between Bankruptcy (P) and all independent variables of X, Z, Y groups. Fig. 8 shows that P has the strongest correlation with X3, Y3, Y4, and X7, and a weak negative correlation with Z2. In addition, the absolute values of correlation between several variables exceeds 0,7 which means that there is multicollinearity. Subsequently, it is necessary to examine all the indicators for normality by plotting the distribution and visually comparing it with the normal distribution, as well as conducting the Shapiro-France test. Thus, all indicators, except X1, X5, Y2, Y1, and Z2, have a normal distribution. For variables X1, X5, Y2, Y1, and Z2, the logarithm of their meanings was used to build the models.

	Bankru-y	X1	X3	X4	X5	X6	Y1	Y2	Y3	Y4	X7	Z1	Z2
Bankruptcy	1.0000												
X1	0.1945	1.0000											
X3	0.8593	0.1792	1.0000										
X4	-0.6879	0.0236	-0.3566	1.0000									
X5	-0.5982	-0.1954	-0.6567	0.0340	1.0000								
X6	-0.4735	0.4421	-0.3243	0.7578	-0.0970	1.0000							
Y1	-0.6102	-0.0783	-0.6941	0.4267	0.1309	0.4694	1.0000						
Y2	-0.6653	-0.2583	-0.6607	0.5756	0.3404	0.4245	0.7235	1.0000					
Y3	0.8644	0.1558	0.8412	-0.5775	-0.6303	-0.4169	-0.6653	-0.7550	1.0000				
Y4	0.8786	0.0776	0.9417	-0.4106	-0.6856	-0.3824	-0.6607	-0.6547	0.8530	1.0000			
X7	0.9246	0.2168	0.8715	-0.6282	-0.6961	-0.3986	-0.6026	-0.7763	0.9450	0.8760	1.0000		
Z1	0.2682	-0.2750	0.1441	-0.2666	-0.2336	-0.4650	-0.0067	0.1836	0.0908	0.2560	0.1460	1.0000	
Z2	-0.1036	0.6699	-0.1655	0.2620	0.0117	0.4589	0.1305	0.1629	-0.0777	-0.2384	-0.1516	-0.1861	1.0000
Z3	0.0468	-0.1759	0.5007	0.4099	-0.2181	0.0627	-0.2830	-0.0637	0.1382	0.4031	0.1256	-0.0687	-0.3312
Z4	0.0667	-0.0469	0.4941	0.3607	-0.0319	0.0054	-0.5001	-0.1144	0.1219	0.3883	0.0656	-0.0818	-0.1190
Z5	0.2679	-0.1450	0.4942	-0.0281	-0.3522	-0.2389	-0.0901	-0.2297	0.3219	0.4253	0.3593	0.0833	-0.3685

  

	Z3	Z4	Z5
Z3	1.0000		
Z4	0.8740	1.0000	
Z5	0.6629	0.3525	1.0000

**Fig. 8.** Correlation matrix.

Dozens of models were built, and the three most predictive models with all significant variables were chosen. The first model (Model A) consisted of three regressors. It consists of operational leverage (Z3), the sales to total assets ratio (X4), and total debt to total assets (logX5). These indicators were chosen because they can show the position of the company

from different sides, namely its debt burden, the ability to generate revenue with a high gross margin and low operational costs, and the ability to use the profit (revenue) in the correct direction. Table 12 shows that all the variables are significant at the 5% significance level. The P-value for the F-statistic equals zero, which means that the model is significant in general. The R-squared value shows that the variables used explain the probability of bankruptcy by 88,35%.

Although Model A is significant, it is necessary to check this model for the correctness of its specification, which, in turn, will ensure that there is no false heteroscedasticity or biased estimates. To do this, the Ramsey test is conducted, which implies constructing an auxiliary regression of the dependent variable on itself, its square, cube, and fourth power, which should be insignificant; in other words, the coefficients for the regressors should be zero. From Fig. 9, we can see that the p-value for F-statistics is less than 0,05, thus H0 for the right model specification is rejected.

Source	SS	df	MS	Number of obs	=	32
Model	1.65663183	3	.552210609	F(3, 28)	=	70.81
Residual	.218368173	28	.007798863	Prob > F	=	0.0000
				R-squared	=	0.8835
				Adj R-squared	=	0.8711
Total	1.875	31	.060483871	Root MSE	=	.08831

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
logX5	-.1897955	.0231158	-8.21	0.000	-.2371462 - .1424449
X4	-.4284931	.0314801	-13.61	0.000	-.4929772 - .3640091
Z3	.0135222	.0030349	4.46	0.000	.0073056 .0197389
_cons	1.092875	.0381219	28.67	0.000	1.014786 1.170965

**Fig. 9.** Model A.

Ramsey RESET test using powers of the fitted values of Bankruptcy  
 Ho: model has no omitted variables  
 F(3, 25) = 17530.93  
 Prob > F = 0.0000

**Fig. 10.** Ramsey test for Model A.

Next, it is necessary to check this model for heteroscedasticity, that is, the heterogeneity of observations with a predominance of variance and error, which leads to bias and inconsistency in the covariance matrix estimation and inefficiency of the estimation results. For greater accuracy, we perform three tests for heteroscedasticity. The critical value of the p-value in these tests equals to 0,05. The first heteroscedasticity test is the Breusch – Pagan test (hettest), which is used to construct the dependence of the square of the residuals on the predicted values of the dependent variable (Fig. 11). The null hypothesis of this test states that the coefficients of the predicted values are zero; in other words, the regression, in general, is insignificant. Otherwise, the dependence of the error square on the predicted values is observed; that is, the error squares are not constant, which indicates heteroscedasticity. This test shows us that the p-value is less than 0,05, which means that Ho about homoscedasticity is rejected and the problem of heteroscedasticity is presented in Model A.

```

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of Bankruptcy

chi2(1)      =    11.02
Prob > chi2  =    0.0009

```

**Fig. 11.** Breusch-Pagan test for Model A.

The second test is the Breusch-Pagan test 2 (hetttest, rhs), which involves constructing a regression of the square of residuals on explanatory variables (Fig. 12). The null hypothesis is similar to the previous test. The result of the second test is the same as in the first one and points on the problem of the heteroscedasticity.

```

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: logX5 X4 Z3

chi2(3)      =    14.09
Prob > chi2  =    0.0028

```

**Fig. 12.** Breusch-Pagan test 2 for Model A.

The White test (imtest) allows us to detect the presence of heteroscedasticity of any form by constructing the error square on the explanatory variables, their squares, as well as all or some of their pairwise products (Fig. 13). The null hypothesis is the same as the hypothesis of the two previous tests. This test also confirms the presence of heteroskedasticity.

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	29.31	9	0.0006
Skewness	18.80	3	0.0003
Kurtosis	0.51	1	0.4747
Total	48.63	13	0.0000

**Fig. 13.** White test 2 for Model A.

The next step is to check the model for multicollinearity, which characterizes the presence of a linear relationship between the variables (Fig. 14). To do this, we will perform the vif test. To detect the presence of multicollinearity, it is necessary to compare the  $R\text{-squared} = 0.8835$  of the model with the value  $1-1/VIF_{\max} = 1-0,89 = 0,11$ . Thus,  $R\text{-squared} > 1-1/VIF_{\max}$ , which means that there is no multicollinearity.



Variable	VIF	1/VIF
X4	1.27	0.786144
Z3	1.22	0.817498
logX5	1.12	0.890383
Mean VIF	1.21	

**Fig. 14.** Multicollinearity test for Model A.

Let us build the second model (Model B), which will consist if the independent variables of model A adding working capital/total assets (X2). Model B presented on the Fig. 15 has all indicators significant on 5% level and is significant in general (p-value of F-statistics equals 0). The variables of this model explain the probability of bankruptcy a bit then Model A, its predictive power is rather high and equals to 89,49%.

Source	SS	df	MS	Number of obs =	32
Model	1.67792782	4	.419481954	F(4, 27) =	57.47
Residual	.197072182	27	.00729897	Prob > F =	0.0000
Total	1.875	31	.060483871	R-squared =	0.8949
				Adj R-squared =	0.8793
				Root MSE =	.08543

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
logX5	-.1700841	.0251647	-6.76	0.000	-.2217177 -.1184504
X2	.1186888	.0694851	1.71	0.099	-.0238828 .2612604
X4	-.4136891	.0316637	-13.07	0.000	-.4786576 -.3487206
Z3	.0126794	.0029772	4.26	0.000	.0065708 .0187881
_cons	1.111614	.038477	28.89	0.000	1.032666 1.190562

**Fig. 15.** Model B.

3 tests of heteroscedasticity have been provided on the Fig. 16. All of them point out the heteroscedasticity problem because p-value is less than the critical value.

The test for multicollinearity shows that the value  $1-1/VIF_{max} = 1-0,205 = 0,154$  is less than R-squared of Model B = 0,8949 which point on the absence of the multicollinearity in this model which is the positive sign (Fig. 17).

```

. hettest
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of Bankruptcy

chi2(1) = 8.87
Prob > chi2 = 0.0029

. hettest,rhs
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: logX5 X2 X4 Z3

chi2(4) = 14.48
Prob > chi2 = 0.0059

. imtest
Cameron & Trivedi's decomposition of IM-test

```

Source	chi2	df	p
Heteroskedasticity	29.72	14	0.0083
Skewness	19.44	4	0.0006
Kurtosis	0.20	1	0.6557
Total	49.36	19	0.0002

**Fig. 16.** Heteroscedasticity tests for Model B.

Variable	VIF	1/VIF
logX5	1.42	0.703144
X4	1.38	0.727246
X2	1.33	0.752429
Z3	1.26	0.795044
Mean VIF	1.35	

**Fig. 17.** Multicollinearity test for Model B.

Ramsey test shows that there are mistakes in the model specification (Fig. 18).

The third model (Model C) will include accounts payable turnover (logY2), change of EBIT in % (Z4), sales to total assets ratio (X4) and total debt to total assets (log X5). From the first point of view, this model can be better than other ones because it additionally takes into consideration the indicators of profitability and changes of EBIT compared with the previous period and the debt burden which can identify if the company have financial problems or not. The results are shown on Fig. 19.

```
Ramsey RESET test using powers of the fitted values of Bankruptcy
Ho: model has no omitted variables
F(3, 24) = 47503.90
Prob > F = 0.0000
```

**Fig. 18.** Ramsey test for Model B.

Source	SS	df	MS	Number of obs =	32
Model	1.73747675	4	.434369187	F(4, 27) =	85.28
Residual	.137523254	27	.005093454	Prob > F =	0.0000
Total	1.875	31	.060483871	R-squared =	0.9267
				Adj R-squared =	0.9158
				Root MSE =	.07137

  

Bankruptcy	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
logY2	.0437732	.0170725	2.56	0.016	-.0087433 .0788031
logX5	-.2102407	.0188294	-11.17	0.000	-.2488754 -.1716061
Z4	.0330897	.0048666	6.80	0.000	.0231042 .0430753
X4	-.4778583	.0309869	-15.42	0.000	-.5414482 -.4142883
_cons	.9497639	.0494168	19.22	0.000	.848369 1.051159

**Fig. 19.** Model C.

Regressors of Model C have the greatest predictive power among all 3 models, and they explain 92,67% of bankruptcies. All the regressors are significant on 5% level. The model is significant in general as the p-value of F-statics equals to 0.

Let us provide 3 tests of heteroskedasticity (Fig. 20). In all test p-value exceeds the critical p-value, which means that Ho is approved and there is homoskedasticity in Model C.

Test for multicollinearity defines that  $1-1/VIF_{max} = 1-0,2197 = 0,7803$  is less than R-squared of the model = 0,9267 which means that there is no multicollinearity in Model (Fig. 21).

```

. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of Bankruptcy

      chi2(1)      =    0.62
      Prob > chi2  =    0.4323

. hettest,rhs

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: logY2 logX5 Z4 X4

      chi2(4)      =    0.64
      Prob > chi2  =    0.9582

. imtest

Cameron & Trivedi's decomposition of IM-test

```

Source	chi2	df	p
Heteroskedasticity	18.49	14	0.1852
Skewness	5.74	4	0.2197
Kurtosis	2.04	1	0.1537
Total	26.27	19	0.1230

**Fig. 20.** Heteroskedasticity tests for Model C.

Variable	VIF	1/VIF
X4	1.89	0.529905
logY2	1.53	0.653729
Z4	1.31	0.763318
logX5	1.14	0.876407
Mean VIF	1.47	

**Fig. 21.** Multicollinearity test for Model C.

The last test will show if there are any mistakes in the model specification. According to Ramsey test there are mistakes because p-value equals to 0 (Fig. 22).

```

Ramsey RESET test using powers of the fitted values of Bankruptcy
Ho: model has no omitted variables
      F(3, 24) = 16790.40
      Prob > F = 0.0000

```

**Fig. 22.** Ramsey test for Model C.

Thus, let us summarize the results of 3 models in the Table 4 and point «1» if the model has the best predictive power, no problems with heteroscedasticity, multicollinearity, mistakes in specification, otherwise – write «0».

**Table 4.** Comparison of 3 models.

Criteria	Model A	Model B	Model C
Heteroskedasticity	0	0	1
Multicollinearity	0	0	1
Specification	0	0	0
Adj R-squared	0	0	1

As Model C is more predictive and does not have problems with heteroscedasticity and multicollinearity, so it is chosen as the best one.

Thus, the scoring model for bankruptcy prediction for the European countries looks like:

$$P = 0,949 + 0,044 \log X_1 - 0,21 \log X_2 + 0,033 X_3 - 0,478 X_4 \quad (4), \text{ where}$$

$X_1$  – accounts payable turnover,

$X_2$  – total debt/total assets,

$X_3$  – change in EBIT in %,

$X_4$  – sales/total assets.

If  $P \geq 1$  – healthy company,

if  $P < 1$  – company has financial problems and the increasing possibility of bankruptcy.

The signs before the variables were easy to interpret. First, the positive sign before  $X_1$  means that the increase in accounts payable turnover does not imply a deterioration in the financial position of airline companies. The negative sign before the debt to total assets ratio ( $X_2$ ) shows that sometimes a high debt burden can be a signal of future bankruptcy. The increase in EBIT for airline companies means that the company develops, and it is profitable, which is why it is a positive sign before  $X_3$ . For airlines, it is better when the sales to total assets ratio ( $X_4$ ) is smaller because airlines tend to have large asset bases financed by revenue. Thus  $H_2$  is rejected.

It is reasonable to apply this model to current research data. This indicates that several companies have a sharp decline in  $P$  in 2020 of less than 1, which is a sign of instability. It is widely known that these companies have serious problems.

Deutch Lufthansa is the first company with  $P=1,53$  in 2019 and  $0,31$  in 2020 is Deutch Lufthansa. At the end of 2020, the Coordinating Board of the company claimed to the German media that they seriously considered the company's bankruptcy instead of government aid. As an advantage of bankruptcy, the Board pointed to the suspension of airfare reimbursement, which was estimated at 1,8 billion dollars. In turn, it could ease the dismissal and closure of loss-making subsidiaries. Currently, there is no new information on a company's intentions.

Second, Finnair's  $P$  in 2019 equals 1,36 and in 2020 it is 0,11. Information about its possible bankruptcy has not been given by the official representatives to mass media, but it is obvious that such a great decline can be a negative sign for the company.

Thirdly,  $P$  of Norwegian Air in 2019 equals to 1,36 and 0,11 in 2020. In 2020, Norwegian airlines claimed bankruptcy because Pandemic-19 caused a crisis in the company because of huge amounts of debt and termination of transatlantic transportation. However, in May 2021, the company officially claimed that it had emerged from bankruptcy and began to work as a regional carrier. The company reduced its fleet threefold and its debt from 156 billion Norwegian crowns to 18 billion.

Air France KLM has the worst situation, which was also announced in all mass media and is known all over the world because of the huge loss in 2020 equaling 7 billion euros. This is the only company in the sample whose  $P$  is below zero in 2020. Nowadays, the French government has tried to help companies become healthy. Last year, it allocated 7 billion euros to Air France to pay its 2020 costs.

For all four companies, the serious decline in  $P$  from 2019 to 2020 is explained mostly by the decrease in sales/total assets and the negative change in EBIT.

The position of Aegean airlines was not crucial in 2020, and  $P$  equaled to 0,9. Only Ryanair had a  $P$  more than 1 and moreover its EBIT was positive in 2020.<sup>3</sup>

## 4.2 Development of the economic approach to assessing the probability of bankruptcy

To start, despite the established regression model taking many variables into account, it does not include two categories of indicators that should be taken into account when evaluating the financial status of the organization and its dynamics.

As a first step in determining the short-term financial stability of airlines, it is crucial to take into account the indication of current liquidity. With its assistance, it is possible to evaluate not only its capacity to repay short-term debts using money from various accounts, but also its capacity to mobilize resources for the repayment of debts with the highest priority and cash for the repayment of the most pressing debts.

It is advisable to take account receivable turnover into consideration because it is important to determine not only how quickly the business pays its creditors but also whether or not its customers pay on time.

Seven financial variables will therefore be taken into account in the model for predicting insolvency for European aviation operators. Following the selection of the indicators, the baseline values will be established. In order to achieve this, the company's data will be split into two groups, with the first group consisting of the years when companies experienced financial difficulties or filed for bankruptcy based on the developed model, and the second group consisting of the times when their financial position was considered to be stable. The normative values will be established so that the average values of the relevant indicators in the second group will serve as crucial values and the values of the indicators in the first group will act as the industry's ideal values.

However, the average of all indicators should not be extracted from the second group, but only those that are worse than the average values of the first group. Thus, the average value in the second group should consist of those indicators that will be less than the average of the first group, except for the turnover of accounts payable and receivables, sales to total assets (according to the industry), Debt to EBITD – for them, the higher the value, the worse the financial position.

Thus, based on the calculations performed, the following critical and optimal values of financial indicators were obtained, which are reflected in the Table 5 along with the standard values of these indicators according to the global international practice.

**Table 5.** Normative values of financial indicators according to the developed model for bankruptcy prediction.

Ratio	Optimal value	Critical value	International practice (max value)
Current liquidity ratio	0.93	0.59	1
Sales to total assets ratio	0.82	2.3	Depends on industry
Total debt to total assets	0.31	0.6	0.4
Accounts receivable turnover (days)	18	43	30
Accounts payable turnover (days)	25	61	30
EBIT change	14%	<0	
Debt to EBITDA	2.6	<0	5

According to the table above, the optimal and critical values for airline companies are generally within the established boundaries of international practice. However, each airline has its own set of characteristics. To begin, the average optimal liquidity ratio is 0.93, which is less than the established normative ratio. It can be argued that, while airlines can be successful in the market, they devote the majority of their resources to non-current assets.

Second, because it varies by industry, the normative value for sales to total assets has not been defined in global practice. Companies with financial problems have a higher level of this ratio than healthy firms, according to the sample of airlines. It can be concluded that airlines have large amounts of total assets, the majority of which are non-current assets, primarily fixed assets (PP&E), proving the assumption of a lower liquidity ratio in comparison to the established in practice.

Third, accounts receivable and payable turnovers are within the established normative values; however, it is important to note that it is necessary to analyze the terms of contracts with consumers and creditors in order to reach the correct conclusion about timely fulfillment of obligations. The indicator of change in EBIT has not been defined in world practice, but the sample shows that healthy companies have increased EBIT from the previous year to the current one, whereas troubled companies have decreased EBIT or mostly negative EBIT and EBITDA values. The debt to EBITDA ratio varies by industry, but it is typically defined between 4 and 5.

The optimal value for European countries, according to the model, is 2,6. As a result, it is reasonable to set the normative upper bound of this indicator at 5.

To summarize, the assessment of the possibility of bankruptcy of European airlines has its own features, such as the definitions of current liquidity ratio and total sales to total assets ratio. As a result, it is prudent to divide the assessment of European airlines' potential bankruptcy into stages.

In the first stage, use the formula  $P = 0,949 + 0,044 \log X_1 - 0,21 \log X_2 + 0,033 X_3 - 0,478 X_4$  to determine whether the company is stable and does not have serious problems ( $P \geq 1$ ) or not ( $P_1$ ) (5).

The method of predicting bankruptcy receives the most attention. If the calculated financial ratio values fully correspond to the industry's optimal values, the company is considered healthy. If the indicators' values coincide with the critical values, it may be an indication of potential financial problems. If the values do not completely match, the analysis should prioritize four regression model indicators. For the airline to be considered healthy, the values of these four indicators must be in the optimal range; otherwise, the company faces a high risk of serious deterioration in financial stability, which could lead to bankruptcy in the future. d the bankruptcy strategy

## **5 Conclusion**

Bankruptcy prediction is a critical issue for a wide range of entities, including company management, investors, creditors, banks, and the government, particularly in the context of economic crises such as the pandemic COVID-19. The airline industry will be severely impacted globally in 2020. There are no actual existing methods of predicting bankruptcy based on industry and region specifics. The current study was devoted to the development of such a model based on actual data from 2016 to 2020 while taking the region factor into account. This model can help all interested parties provide timely assessments of financial problems and make sound decisions about needed assistance and the company's overall future.

Thus, in this study, the industry-specific features of the European airlines were identified and analyzed. This was achieved by conducting a multi-step analysis. First, 11

financial indicators used in the existing models and 5 additional ratios which can influence the bankruptcy appearance according to the author's assumption, were calculated for 7 large European airlines. Then, based on the calculated coefficients, several regression models were constructed, among which the best one was determined, containing the most significant indicators for the industry:  $P = 0,949 + 0,044 \log X1 - 0,21 \log X2 + 0,033 X3 - 0,478 X4$ , where

X1 – accounts payable turnover,

X2 – total debt/total assets,

X3 – change in EBIT in %,

X4 – sales/total assets.

If  $P \geq 1$  – healthy company,

if  $P < 1$  - company has financial problems and the increasing possibility of bankruptcy.

In addition, three more economic feasibility indicators were added to the review. The optimal and critical values for the industry were then calculated using all seven coefficients. They were then compared to international practice standards, based on which the characteristics of the values of the indicators of current liquidity and sales to total assets were identified.

Following that, approaches for assessing the likelihood of European airline bankruptcy were developed. So, first, the mathematical scoring model  $P = 0,949 + 0,044 \log X1 - 0,21 \log X2 + 0,033 X3 - 0,478 X4$  should be used to determine whether the company is stable in the current year ( $P > 1$ ) or not ( $P < 1$ ).

Then it was discovered that it is appropriate to recognize the company as healthy in two cases: 1) If the values of the calculated financial indicators fully correspond to the established optimal ones for the industry.

2) If the values of the four regressors used in the regression model fully correspond to the optimal ones.

Otherwise, the company faces deterioration or even future bankruptcy.

The outcomes of the three hypotheses are different.  $H_0$  is accepted as the global existing model of European company bankruptcy prediction is inaccurate inside the prediction of European airlines as several indicators are insignificant.

$H_1$  is rejected because the existing model of European airline bankruptcy prediction developed in 2012 no longer applies to current reality, and some ratios have no influence on their bankruptcy.  $H_2$  is rejected because the airlines have a low sales-to-total-assets ratio because they have a lot of PP&E.

To summarize the findings of this study, the goal has been met because approaches for predicting bankruptcy for European airlines have been developed, allowing interested parties to more accurately determine the financial position of companies in this industry, thereby reducing potential credit risks.

The current study will be part of a larger global investigation of other countries' airline companies to prove or disprove several hypotheses. The first is that airline companies in different regions require different approaches to predicting bankruptcy. The second hypothesis calls for the development of a global model of bankruptcy prediction for all airlines from various regions, with the assumption that the global model has less predictive power than the regional models.

The third will be tested if there are more cases of airline bankruptcies due to the pandemic COVID-19 by the end of 2021, and it will be assumed that the pandemic crisis differs from the crisis of 2015 and reflects their financial position in a different way, and the significant indicators or signals of bankruptcy are not the same as in 2015.

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