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A comparative analysis of Altman's Z-score and T. Jury's cash-based credit risk models with the application to the production company and the data for the years 2016-2022

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Abstract

Research Questions: In the present paper the author answers the following research questions: 1) What are the potential strengths of the credit risk model based on the cash flow principle? 2) What are the weaknesses of the accrual-based credit risk model? 3) What are the benefits of the combined use of both cash-based and accrual-based credit risk modeling methods when analyzing companies?

Motivation: nowadays there are no researches comparing the accrual-based credit risk model to a cash-based credit risk model with the application to a production company trading its shares on Stock Exchange. However, for investors, auditors and financial institutions it is important to know if there is a difference between these two models in the interpretation of analysis results, and determination of prebankruptcy stage of the company and credit risk default.

Idea: in this paper, the author has focused on the comparative analysis of the cash-based credit risk model and the accrual-based credit risk model. The author applies it to the case of a manufacturing company and compares the effectiveness of determining the probability of default using a cash-based credit risk model and an accrual-based credit risk model.

Data: the data analysed is obtained from the annual reports, managerial reports and auditor's reports of Linas Agro Group for the years 2016-2022. The company information is taken from Nasdaq Baltic where Linas Agro Group has its shares traded.

Tools: mixed research methods were used, combining quantitative calculations with analysis based on qualitative information. The author elaborates on the cash-based credit risk model based on the improved Timothy Jury's template. The accrual-based model chosen for comparison and analysis is Altman's Z-Score model.

Findings: The results of the study have shown that the cash-based model is more effective in determining credit risk and default probability. The cash-based model indicated a high-

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risk default for the manufacturing company in four years out of seven years, while Altman's Z-Score showed the company to be in the moderate risk grey zone in five years out of seven, and the two last years the model indicated the company in the green zone. The author suggests to financial institutions, financial managers, and investors using a cash-based credit risk model or combination of it with the accrual-based model.

Contribution: the paper contributes to the knowledge about the comparison of cash-based and accrual-based credit risk models and emphasizes their strengths and weaknesses. It helps investors, auditors, business owners, and finance professionals to make a decision about which credit risk model to use for the analysis to determine the pre-bankruptcy state of the company, avoid bad loans and improve investment decision-making. It also encourages the academic society for further research and comparison on the topics of accrual-based and cash-based credit risk models in the strive to develop the ultimate credit risk model capable to analyse the data as precisely as possible.

Keywords: cash-based analysis, accrual-based credit risk model, credit risk, probability of default, credit risk modelling.

JEL codes: M41

1. Introduction

It is evident that nowadays there is a knowledge gap in the area of cash-based methods in credit risk modeling. The lack of knowledge in this area among professionals can be the reason why the traditional accrual-based methods prevail in the analysis despite some weaknesses in these methods (Jury, 2012). However, the cash-based approach with the cash-based indicators and ratios possesses certain benefits which can serve to a more precise and early determination of the company's pre-bankruptcy stage and the possibility of credit risk default. The necessity to expand the knowledge about cash-based analysis methods and the demand for the analysis methods with high precision should lead the academic society to the development of knowledge about cash-based credit risk analysis. Therefore, the author of this paper represents a comparative analysis of the accrual-based and cash-based methods applied to a production company case.

Many researchers use secondary data without questioning the correctness of the data source. This leads to the possible noise and error in the analysis, outcomes and conclusions of the studies, which takes a tremendous scale with the increase in the number of companies analyzed. The use of secondary data allows for saving time for scientific research and analyzing the big volumes of data with Eurostat as one of the most popular sources of such data. However, when analyzing such data, there is only a quantitative side of the research performed, without qualitative data that could explain the reason for a particular number and ground the outcomes of such studies.

Contrary, the focus of the present paper is an in-depth mixed methods study of primary data from the financial statements, managerial and auditors reports of a single production company for seven years.

The aim of the present paper is to compare the features of Altman's Z-Score model (accrual-based) with the reworked template of Timothy Jury (cash-based) applied to the financial data of one manufacturing company case. Based on this to find out the strengths and weaknesses in the analyses performed through these two methods, whether the cash-based template or an accrual-based credit risk model is more correct in the estimation of the financial position of the company, proving the findings with the analysis of the managerial and auditor's reports. The reliability of the conclusions of the present paper is proved by the auditor's reports as it becomes evident from the chapter dedicated to the comparative analysis. The author emphasizes that the empirical analysis of many companies with the use of the existing models based on secondary data from Eurostat was not the aim of this research.

For further publications, the author analyzed 200 manufacturing companies in the US, UK and EU, therefore the empirical analysis with explicit statistical data will be presented in the following papers after the necessary theoretical background is built up with the present paper. The Timothy Jury's reworked template presented in this paper can be used as an independent model for credit risk default analysis. However, the author used it to extract the key element, total net (debt) to cash, in order to integrate it into the new credit risk model together with other elements of solvency and liquidity, including macro-economic elements, which will be presented in future papers.

The present paper contributes not only to the academic knowledge about the comparison of cash-based and accrual-based methods of analysis but also serves the benefit of practitioners. With the increased instability of the modern economy, credit risk analysis becomes a crucial part of daily operations and the precision of such analysis is key in decision-making for financial managers, auditors, investors, company owners and other finance practitioners. Estimation of solvency and liquidity of the vendors and customers with high precision helps to plan operations and conclude contracts only with the most reliable counterparts avoiding bad loans, unpaid invoices and disruption of supply.

There is also a connection between bad loans and macroeconomic factors. This sensitivity of non-performing loans varies from one sector to another, with the most sensitive sectors where banks finance an important part of working capital (Istrate & Ionescu, 2018). The estimation of the pre-bankruptcy state of the company is also crucial for the economies in general. The consequences of some companies' bankruptcies can not only threaten banks, creditors, managers and investors but can also lead to profound crises (Elmarzouky *et al.*, 2022).

However, some financial managers possess enough skills and knowledge to manipulate traditional financial statements in the favour of their companies in order to receive additional funding or a desired contract (Jury, 2012), which makes it difficult for their counterparts to estimate their creditworthiness with the use of accrual-based credit risk model analysing traditional financial statements. Therefore, the new method is in demand, which would allow analysing of the creditworthiness of the companies with higher precision and with diminished risk of financial data manipulation. The cash-based credit risk analysis represents such a method because cash-based statements are less prone to manipulations from the side of financial managers. The existing studies show that cash flow statements provide more precise information about a company’s solvency and liquidity than traditional financial statements (Mills & Yamamura, 1998).

The present paper compares Altman’s Z-Score accrual-based model to a cash-based Timothy Jury analysis template reworked by the author. Both methods are applied to the financial data of a publicly listed production company and the results of the credit risk analysis are compared between the accrual-based and cash-based methods.

2. Literature review

First and foremost, it is important to emphasize the timeline of the company’s financial problems leading to credit risk default and bankruptcy. First, the company’s efficiency and profitability start to decline. This leads to solvency and liquidity problems. According to Altman and Hotchkiss (2006), technical insolvency is when a company is unable to meet its current obligations, which indicates a lack of liquidity. If the company does not improve its financial indicators, it will reach the pre-bankruptcy stage. If a company is unable to meet its obligations to creditors, especially banks and other financial institutions, then credit risk default occurs. There are two types of defaults: technical and legal. When the debtor violates the agreement conditions with the creditors the technical default takes place, while the legal default takes place when an entity misses a scheduled loan payment. (Altman & Hotchkiss 2006).

After the credit risk default of the company, the situation can develop in two ways. The first option is to restructure and reorganize the company so that the company continues to operate on a going concern basis. The going concern principle assumes that the company continues its operations and will not be forced to cease operations and liquidate its assets in the nearest future so that the recognition of some expenses is deferred until a later period. (ISA 570, 2016). The goal of the reorganization is to ensure that the rehabilitation of the company would be fair (with the proper priority of claims) and feasible (fixed costs of the recapitalized company will be realistically met) (Altman & Hotchkiss, 2006). In the second option, the bankruptcy of the company takes place and the going concern principle is cancelled, followed by the post-bankruptcy process going on by the cash principle based on the bankruptcy laws. Altman and Hotchkiss (2006) describe bankruptcy as a chronic situation when a company's liabilities exceed the fair value of its total assets, resulting in its negative real net worth. There is interesting research on bankruptcy and insolvency by Onakoya and Olotu (2017), where the terms are analysed based on their origin. The researchers state that the term "bankruptcy" takes its origin from the words *bankus* (bench or table) and *ruptus* (broken), meaning the inability of a banker (transacting his business in a marketplace on a workbench) to meet his contractual obligation. They also stipulate that bankruptcy law aims to protect and relieve the indebted entities (Onakoya & Olotu, 2017), leading to the next step – liquidation. As noted by Altman and Hotchkiss (2006), liquidation is economically justified when the value of the individually sold assets exceeds the capitalized value of the assets in the market with key variables such as time and risk in this case. It is important to outline why credit risk analysis is crucial for economic and financial industries. The researchers state, that "the credit risk analysis aims to reduce future losses by estimating the potential risk and eliminating the newly proposed credit if the risk is greater than a defined tolerance value. In this respect, it is essential to identify the main factors determining this risk in order to manage it effectively" (Istrate & Ionescu, 2018). Credit risk is defined as the inability of the borrower to keep their promise of timely interest payments or the repayment of principal at maturity. And it is one of the most dangerous and common risks that a financial institution as well as other financial industry players might face (Khemakhem & Boujelbene, 2015).

Cornelius Casey and Norman Bartczak (1985) elaborated on one of the key research on the use of operating cash flows to predict financial distress. Although their study using multiple discriminant analysis suggested that operating cash flows themselves do not possess incremental predictive power over accrual-based ratios, however, the researchers concluded that cash flows have a huge potential in various analyses. This study was a good step forward for further researchers looking for the area of application of cash-based data for the prediction of financial indicators of the firms. Schroeder, Clark, and Cathey in their book underlined the importance of the operating cash flow generation ability of an enterprise as an indicator of health and degree of risk of investment into an enterprise (Schroeder et al., 2014).

2.1. Credit risk models and their types in the context of accrual-based accounting

The list of credit risk models is quite extensive, and it continues to grow, because none of the invented models is perfect, as far as the author of this research concluded by performing qualitative research on this topic. Fernandes (2005) classifies the three main approaches to credit risk modeling among which the first two can be used for companies with traded equity or debt:

1) Structural models;
2) Reduced-form models;
3) Credit scoring models. Used for privately held firms.

For structural models, the major theory contributors are Merton, who proposed Merton option pricing model in 1974, and Black and Scholes who extended it together with Merton. Merton investigated the valuation of corporate debt in three states: coupon-bearing debt, callable debt, and the most emphasized zero-coupon debt. (Sundaresan, 2013). This model requires information about the company's assets and liabilities, as it presumes that credit risk occurs when the assets fall below the company's debt (Merton, 1974). Another extension of Merton's model suggests a developed reduced-form model based on the discounted cash balance as a primitive variable (Capinski, 2007).

Jarrow and Turnbull created the reduced-form model in 1995 (Jarrow & Turnbull, 1995), and extended by Duffie and Singleton in 1999 (Duffie & Singleton, 1999). The model analyses the interest rates and uses dynamic and multi-factor analysis for the calculation of credit risk. It was very useful for financial institutions, as it has shown also the performance of credit risk investments under different interest rates and with little information on the company's financial situation available (Jarrow &Turnbull, 1995). In other words, this model possesses quite a broad view and does not look into each company closely (Deventer, 2012). With the growing volume of data and the risks of subjective judgments of analysis, the credit scoring models are the most sought-after models for the assessment of credit risk and credit classification of individuals and small companies. The credit-scoring model is a risk management tool that is constructed based on historical data, estimating the probability of default of the requestor assigning the score (Kyriazopoulos, 2019). There is evidence that through credit scoring the accuracy of credit decision-making is improved (Vidal & Barbon, 2019), which positively affects the financial sector overall.

Kyriazopoulos (2019) listed several empirical methods of credit risk evaluation used by American banks as the tools for default prediction and creditworthiness assessment:

- Five C method. The method included both qualitative and quantitative measures for the estimation of the following factors:
  - "Character" reflects the credit history of the borrower;
  - "Capacity" is shown by the borrower's debt-to-income ratio;
  - "Capital" is the amount of money that the borrower possesses;
  - "Conditions" expressing the purpose of the loan, its amount, and interest rates;
  - "Coverage" or collateral is an asset backing the loan.
- The "LAPP" method, estimates liquidity, activity, profit, and potential, with an emphasis on profitability (Abukarsh & Abumwais, 2017).

- "Credit-Men" method, which was not explicitly described by the author.

It is important to mention the invention of the Credit Metrics methodology, which implies both quantitative and qualitative techniques. JP Morgan's Risk Management Research division invented this technique in 1977. The current version of Credit Metrics is based on the Hull-White pricing framework with default valuation and collateral included in the calculation account for non-default as well as used-estimated recovery rates (Credit Metrics, 2007). The methodology is described more thoroughly in the technical document (Credit Metrics, 2007), the most important fact to mention is that migration analysis is one of the fundamental techniques used in Credit Metrics. Although Credit Metrics is a leader in the field of risk management analytics, for this research the author will not use this methodology, because it involves also qualitative data, which cannot be withdrawn from the cash flow. The financial ratios methodology in the default prediction based on the univariate statistical approach was fundamental. Further, in 1968 Altman used multiple discriminant analysis (MDA) statistic techniques to develop his Z-Score model (Altman, 1968), which will be discussed more in-depth further in the current paper. However, it is important to admit that Altman was the first who attempted to create a prediction model for bankruptcy prediction of the companies (Manousaridis, 2017), which of course was followed by criticism and intentions to improve. Some researchers stated that the validity of results by discriminant analysis technique "depends on their restrictive assumptions in case of the assumption of normality of the distribution of each of the variables used and the assumption of independence between them" (Khemakhem & Boujelbene, 2015). Ohlson, who claimed that the score possesses an intuitive interpretation, which is not always relevant, that methods of data collection are not perfect, and even more (Ohlson, 1980), criticized Altman's model. Ohlson created logit analysis in an attempt to suggest an alternative to Altman's discriminant model, stating that logit analysis assigns the firm to the predetermined population, based on large sample theory, and simply finds the probability of default.

2.2 New machine learning techniques in bankruptcy prediction

Nowadays, there are various techniques of machine learning, and they are becoming more popular with the growth of the data volumes and therefore develop. The author selected a few methods for a brief overview in this chapter. Among a variety of supervised machine learning methods, the Deep Feedforward Neural Networks are quite advanced because they can learn patterns of input data through structures of mathematical functions to correctly input data into related outputs. They perform both classification and regression tasks (Goodfellow *et al.* 2016). Researchers highlight several popular packages, such as Python-based Tensflow by Google and PyTorch by Facebook, which due to the regularization of neural networks through drop-out and Lp norm methods constitute a comprehensive feedforward network to predict bankruptcy (Shetty *et al.* 2022).

Support Vector Machine (SVM) is a valuable method for data classification, where the kernel function allows the transformation of the original data into high-dimensional data to ensure the separability of data groups (Qu *et al.* 2019). Even if different classes overlap, SVM has a strong classification efficiency because the SVM classifier always finds a decision boundary and the optimal boundary to classify new data points based on which side of the decision boundary their coordinates lie (Shetty *et al.* 2022). Neural Networks (NN) is currently one of the most used techniques; it is like human neural processing and represents is an inspiration for other computational methods. NN contains several layers, where the first layer is determined by the input variables and the last layer produces the output variables, which in most cases represent the tag or label of each sample. This method is widely used by researchers for bankruptcy prediction, credit scoring and credit data classification (Qu *et al.* 2019). Linear regression is a popular mathematical tool in statistics and econometrics, and it can answer a variety of questions or business issues expressing the linear relationship after feature mapping, and even complex nonlinear models can be linearized, therefore the model is not prohibitive, comprehensive and widely used by the researchers (Chow 2017). It is important to emphasize that due to its nature of taking continuous inputs and outputting a continuous variable, the linear regression is useful for predicting a company's financial distress, thus if there is not enough cash flow to cover the deficit of the negative predicted profit, then the likelihood of entity's bankruptcy is high (Chow 2017).

In my opinion, with machine learning methods, it is important not only to choose the model to use, but also to ensure that the input is correct, leading you to the correct output. Nowadays, researchers mostly use accrual-based input for analysis. Sometimes cash-based input elements are added. However, in addition to having knowledge in IT and quantitative data analysis, it is important to understand fundamental principles of finance and accounting, as well as to combine a full finance and accounting education with practical experience in these fields.

2.3 Comparing the cash-based model to the accrual-based credit risk model

Comparing the cash-based method to the accrual-based credit risk models, the major weakness of the accrual-based models is the possibility that the data in the statements were manipulated. A practice of rewarding managers with incentives can increase the risk of financial statements manipulation in the financial statements by managers either manipulating the existing rules or financial statements or by deciding on the accounting rules that favor them (Hendriksen & Van Breda, 1992). In practice application, it is called the "bonus plan hypothesis" if the net income is increased in a certain period at the expense of later periods, the managers' performance bonuses are related to the size of profit. Another example of manipulation of accounting rule is the choice of depreciation method. Thus, when the earnings for the period are not as high to receive the bonuses, managers can write off everything they can in that less favorable period to increase the probability of positive net incomes in the upcoming periods by choosing the straight-line depreciation method over the accelerated depreciation. (Hendriksen & Van Breda, 1992)

Another example is the research of Mirjam Einstein (Einstein, 2021). The researcher took for the analysis of the bankrupt companies only the accrual-based data for their unique matrix containing ratios. The matrix was based on a system-integrated analysis worked out by the Estonian professor Uno Mereste and developed further by combining the system approach with matrix modeling and the theory of index numbers (Alver & Startseva, 2013; Siimann & Alver, 2015). The result of such research showed that companies had a healthy financial state, although the companies were bankrupt and liquidated (Einstein, 2021). This is a sign that the financial managers and accountants of those companies manipulated accrual-based financial statements of the bankrupt companies before their bankruptcy to hide the solvency, liquidity, and profitability issues. Einstein has done great research. Although the goals of the research were not reached, the model was created, which can indicate the manipulations with accrual-based statements. This raises a red flag and calls for immediate detailed investigation of such cases.

3. Methodology of research

This research uses mixed methods of research: qualitative methods of research and quantitative methods of research. A qualitative study of numerous research papers, books, and dissertations on the topics of credit risk, financial analysis, and cash flow analysis provided the author with a solid theoretical background for this research. Namely, this qualitative research contributed to the understanding of cash flow statement components and purpose, the nature of credit risk and existing credit risk models, as well as their characteristics. There is no perfect credit risk model currently. However, after the thorough analysis of theoretical input gained through qualitative research, the author has chosen one accrual-based model and one cash-based model to compare their usefulness to the financial institutions in the prediction of credit risk default. Machine learning methods have not been chosen for this analysis because they require several components that are not covered in this paper. The present paper serves a different purpose of comparing the reworked template of

Timothy Jury with Altman's Z-Score model based on the case of one manufacturing company comparing the results with in-depth analysis of the financial statements. For the credit risk analysis of the manufacturing company, the author has chosen purely quantitative credit risk models, without any qualitative parameters, because in this research the author is interested in the comparison of the level of trustworthiness of the basis of the financial statements of the models (cash basis versus accrual basis). The author has chosen Altman's Z-Score model for manufacturing companies (see Formula 1), as the ancestor of accrual-based quantitative models and one of the most popular and widely used in financial institutions nowadays (Altman, 1968; Sajjan, 2016):

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.999X5, \quad (1)$$

where:
X1 = working capital / total assets;
X2 = retained earnings / total assets;
X3 = earnings before interest and taxes / total assets;
X4 = market value of equity / total liabilities;
X5 = sales / total assets.

To apply Altman's Z-Score model, the author will pick the necessary values from the income statement and balance sheet of the company, representing the accrual basis of analysis, and will insert them into ratios from X1 to X5 in Formula 1. As an output of the model application, the author will get the score, which will classify the company into one of three categories: red (high credit risk), green (low credit risk), and grey (ordinary credit risk). Important to mention that one should not do this analysis for one year only, only a minimum of five years of analysis can show a more trustworthy result, because sometimes if the company purchases tangible and intangible assets, it can show a decrease in the score on that particular year. As the cash-based credit risk model, Timothy Jury's template was chosen and reworked. A more detailed description of the model and the improvements done by the author is represented in the previous publication (Litvinenko & Alver, 2023).

Timothy Jury has chosen certain cash flow data indicators to serve the credit risk analysis through his template so, that those indicators are compared for several years. The indicators taken from the statement are listed in Table 1: cash generated from operations as a starting line, deducting generated from net working assets, deducting net CAPEX, and deducting taxation paid in the period. These lines result in the line "cash available to satisfy capital providers". Further, the net interest and net dividends are deducted resulting in the line "cash available for debt service". The next line in the template is "total net debt in cash", and the last line is "number of years to repay" which is finalizing the template. (Jury, 2012)

Table 1. Indicators of Jury's template

Action	Line
Starting line	Cash Generated From Operations
(Deduct)	(Invested In) / Generated From Net Working (Current) Assets
(Deduct)	Net Capital Expenditures
(Deduct)	Taxation Paid In The Period
Equals to	Cash Available To Satisfy Capital Providers
(Deduct)	Net Interest
(Deduct)	Net Dividends
Equals to	Cash Available For Debt Service
Starting line, divide by line above	Total Net Debt (-) In Cash
Equals to	Number Of Years To Repay

Note. Source: Jury (2012)

It is important to mention the classification criteria. Thus, if the number of years to repay the debt is from 0 up to 6 years, it shows that the company is healthy and mature. When the number of years to repay ranges from 6 to 10 years, the leverage of the company is high and cash flow is fully utilized. Finally, if the number of years to repay is more than 10 years, there is too much debt. Jury states that restructuring and business disposals might be required to reduce debt, which speaks of the high credit risk. (Jury, 2012). Timothy Jury has created a template comparing values for seven years and after several mathematical manipulations getting the number of years to repay the debt. The higher the number of years to repay the debt, the closer the company is to credit default. Table 2 below shows the summary of outputs. The healthy number of years to repay is from 0 to 6 years. (Jury, 2012)

Table 2. Summary of the Jury's credit risk template outputs

Characteristics	Jury's Template
High credit risk. Marked as a red category.	More than 10 years to repay the debt.
Ordinary credit risk. Marked as a grey category.	From 6 to 10 years to repay the debt.
Low credit risk. Marked as a green category.	From 0 to 6 years to repay the debt.

Note. Source: Jury (2012)

Thus, as visible from Table 2, according to Jury's classification, zero to six years to repay the debt means a strong mature company without problems with solvency and liquidity and strong profitability from its major business activities. Jury's six to ten years to repay the debt, meaning the company acting normally, has the ability to cover the debt, but has small issues with its solvency, liquidity, and profitability. However, such a company still accumulates positive cash from operating activity. Jury's more than 10 years to repay the debt, especially dangerous if classified as "never". This means that the company has a negative value of net cash flow from operations. Such companies have serious problems with solvency, liquidity, and especially with profitability, having high chances of bankruptcy and a high probability of credit default, inability to repay the debt provided by the financial institutions. There are several advantages, specified by Jury regarding the use of his template (Jury, 2012):

- The analysis using the template shows the actual cash available for the interest and debt service.
- The template indicates the cause of the problems with cash if any.
- The cash flow values summarized based on several years show the historic effects of the industrial and economic cycles.

The template is a valuable invention for companies and financial professionals because the cash available for the service of debt is not shown in the financial statements, though it contributes a lot to the credit risk analysis of the company. The author will compare the results of this accrual-based model to the results gained with the breakthrough cash-based model created by Timothy Jury. Timothy Jury has created a template comparing values for seven years and after several mathematical manipulations getting the number of years to repay the debt. The higher the number of years to repay the debt, the closer the company is to credit default. The healthy number of years to repay is from 0 to 6 years, the author will mark it as a green zone, a red zone as more than 10 years, and a grey zone will be from 6 to 10 years (Jury, 2012). Table 3 summarizes the features of both credit risk models used in this research.

Table 3. Summary of the usage two credit risk models

Characteristic	Altman's Z-Score for manufacturing firms	Jury's Template
Basis	accrual-based	cash-based
Number of years analyzed	seven years	seven years
High credit risk. Marked as a red category.	Z-Score less than 1.81	more than 10 years to repay the debt.
Ordinary credit risk. Marked as a grey category.	Z-Score from 1.81 to 2.99	from 6 to 10 years to repay the debt.
Low credit risk. Marked as a green category.	Z-Score more than 2.99	from 0 to 6 years to repay the debt.

Note. Source: Altman (2018) and Jury (2012)

As visible from Table 3, the models are comparable. As a result of applying the accrual-based and cash-based models the company may be classified:

- both as a solvent;
- both as insolvent;
- show different results.

If accrual-based and cash-based credit risk models show different results, this would represent the most interesting option for the investigation. The author will investigate, what could cause different results for the application of these two models. To illustrate the comparison of accrual-based and cash-based credit risk models in a case study, the author has chosen for analysis the financial statements of Linas Agro Group (Linas Agro Annual Report, 2016/2017).

The company produces milk, poultry, grain, and oilseeds for export in Baltics and Scandinavia, as well as supplying certified seeds, fertilizers, machinery, and plant protection products to the farmers. Linas Agro Group is a publicly listed company with its shares traded at Nasdaq Baltic (Nasdaq Baltic, 2021). It is important to mention that Linas Agro Group's financial year ends on June 30.

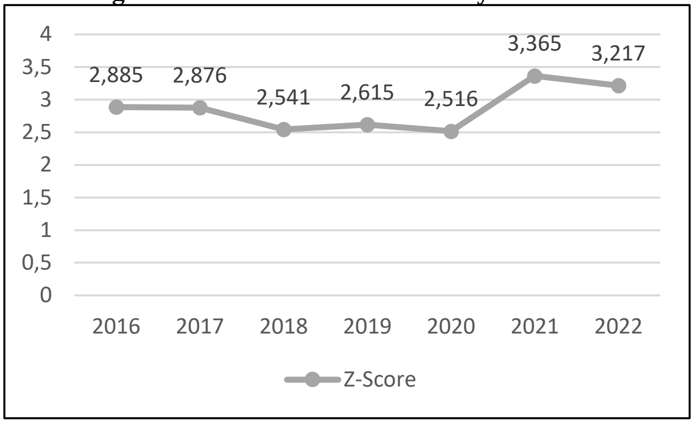
4. Comparative analysis of accrual-based to cash-based credit risk model

This section will start with the application of the Z-Score model and analysis of Linas Agro's accrual financial statements (income statement and balance sheet) with the Z-Score model. In addition, the market value of equity data was taken from the open stock exchange listing and annual report. After analysing company data with an accrual-based model, the author proceeds with the analysis of the cash-based model using Jury's template improved and reworked by the author. Altman's Z-score calculations are represented in Appendix 1.

To review the results of the calculations, Figure 1 includes the compilation of the results of the Z-Score model application to visualize the outcomes. As it is visible from the calculations, in the years 2016–2020 all Z-Score values are ranging between 1.81 and 2.99 indicating that in all years the company is located in the grey zone, closer to the upper part of the grey zone.

The smallest Z-Score is 2.516 in the year 2020 and the highest value was gained in the year 2016 with a score of 2.885. The trend of decrease in the Z-Score value is visible throughout the years from the upper grey zone to the middle grey zone. One of the lowest values as shown in the year 2018. In the years 2021 and 2022 the company moved to a green zone with a value of Z-Score 3.365 in the year 2021 (the highest Z-score value for all seven years of research) and 3.217 in the year 2022. Several elements had the strongest influence on Z-Score behavior. Further, the author reviews the X1 variable. Since working capital is calculated as current liabilities (CL) less current assets (CA), the author has decided to extract and depict these three components into the graph for analysis. Moreover, the current liabilities component is the part of total debt, which will be considered more in detail in the second part of this chapter during the application of the cash-based credit risk model. Figure 2 assists in this analysis.

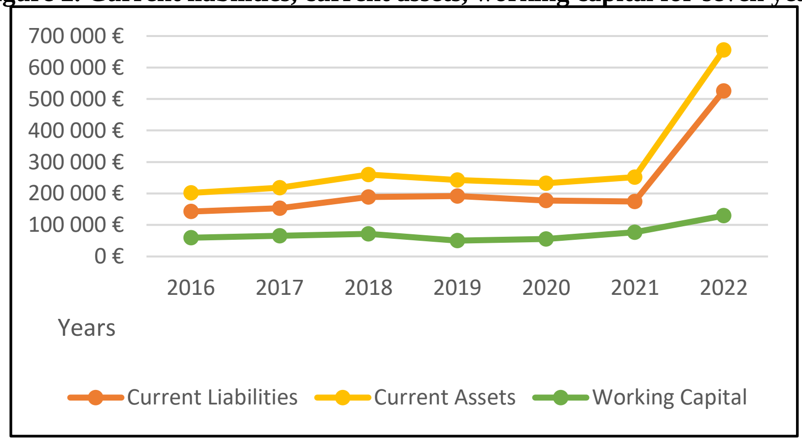
Figure 1. Altman's Z-Score seven-year results



Note: author's calculations based on Appendix 1

Explaining the low value of working capital in the year 2019, Figure 2 shows that the level of current liabilities has significantly grown in the year 2019 striving to the maximum value for the years 2016–2021 and reaching its maximum value in the year 2022. It is important to review Figure 2 more in detail, as it gives some hints on the origin of certain Z-Score values.

Figure 2. Current liabilities, current assets, working capital for seven years



Source: author's calculations based on Linas Agro Financial Statements

Current liabilities continuously grow from the year 2016 to 2019, and only in the years 2020 and 2021, they started to decrease, and then in 2022, they have a sudden increase striking the highest value for the seven years of research. According to the managerial report for the year 2016, the borrowing increased as short-term loans to finance trade activity (Linas Agro Interim Report, 2016/2017). The total amount of the loan portfolio grew in the year 2018, due to increased stocks and debtors (Linas Agro Interim Report, 2017/2018).

The managerial report explains the decrease in current liabilities in the year 2019 as the result of the decrease in the financial loans portfolio due to the diminished amount of stocks and accounts receivable (Linas Agro Interim Report, 2018/2019). The increase of current liability in the year 2022 is supported by the annual report, stating that "As at 31 June 2022, the Company reported a net current liability position of EUR 53,031 thousand. Most parts of the liabilities are borrowings from related parties and the amount of EUR 42,290 thousand of syndicated loan liabilities, which were accounted as current liabilities because of non-compliance with the covenants (Note 20).

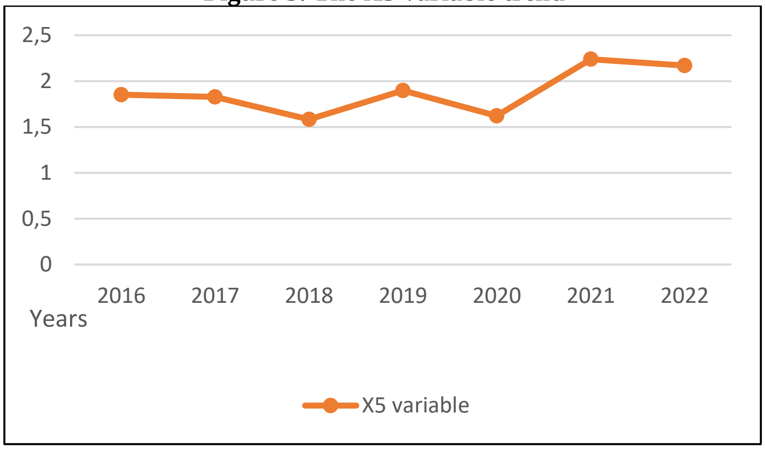
As at the date of issue of these financial statements, the Company has received a waiver from the Bank, stating that does not intend to terminate the borrowing agreement and/or related borrowing agreements. In addition, the Company is able to ensure timely fulfilment of its remaining current liabilities with receivable dividends from earned and distributable profit of subsidiaries. The financial statements have been prepared on a going concern basis." (Linas Agro Group annual report 2021/2022). According to the annual report, a significant part of assets was pledged to banks as collateral for the loans, as stated in the report "as at 30 June 2022, part of inventories of the Group with the carrying value of EUR 128,822 thousand (EUR 61,544 thousand as at 30 June 2021) were pledged to banks as collateral for the loans (Note 20)." (Linas Agro Group annual report 2021/2022, p. 56).

As visible from Figure 2, current assets have also been growing aligned with current liabilities until the year 2018, but it is important to mention that in the year 2019, they have shown the reverse result starting to fall and continuing the decrease in the year 2020. In the year 2021, current assets started to increase and reached their maximum in the year 2022 for all seven years of research. As it is evident from the balance sheet of Linas Agro Group the significant increase in the current assets in the year 2018 is caused by the increase in inventories and trade receivables. The decline in current assets in the year 2019 is caused by the decrease in inventories and cash (Linas Agro Group Annual report, 2018/2019). In the years 2021–2022 based on the balance sheet data, the current assets increased due to the increase in crops, livestock (poultry), inventories, current prepayments, accounts receivable, cash and cash equivalent.

If considering the working capital line, there is a slight growth from the year 2016 until the year 2018 and a sudden fall in the year 2019. Existing empirical research confirms "the importance of the working capital, stating that cash-flow data have incremental information content over accrual earnings data and that cash-flow data are superior to changes in working capital information" (Bowen et al., 1987). Thus, working capital has shown a deep simultaneous fall with current assets in 2019 while liabilities were still growing. However, current liabilities started to decrease in the year 2020 resulting in the working capital's slight growth in the same year. In the years 2021 and 2022, the working capital started to increase due to the significant increase in current assets and current liabilities. Thus, one of the elements that influenced the Z-Score fall in 2020 was a current liability from the X1 variable. The author finds it important to review the X5 variable. This variable is calculated as sales divided by total assets. This element is one of the most significant components of Altman's model, because it is the only one whose value exceeds 1, and the change of this value influences the final Z-Score the most. Figure 3 shows that the dramatic falls in sales of Linas Agro Group happened in the years 2018 and 2020 followed by a significant increase in the years 2021 and 2022 exceeding the value of 2.

To explain the fluctuation of the X5 variable the author analyses the sales data of Linas Agro, because sales are one of the elements that affect X5 movements, and managerial reports provide sufficient information about sales changes. According to a managerial report, in the year 2018 sales dropped down compared to the year 2017 due to low grain prices globally and imposed duties on certain products in import markets (Linas Agro Interim Report, 2017/2019). The total sales volume has also dropped due to the decrease in the harvested area and severe weather conditions (Ibid.).

Figure 3. The X5 variable trend

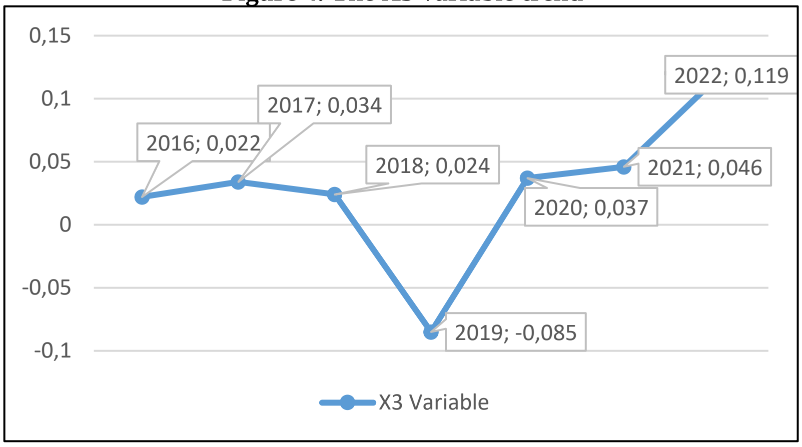


Source: author's calculations based on Appendix 1

As visible from Figure 3 the X5 element increased in the year 2019, which is caused by the increase in sales. The managerial report supports this statement, explaining that because of the large product portfolio, Linas Agro increased its sales volumes (Linas Agro Interim Report, 2018/2019). However, in the year 2020 Figure 3 shows another drop of X5, which is explained by the sales volume decrease of Linas Agro Group by 12% (Linas Agro Interim Report, 2019/2020). However, in the years 2021 and 2022 the significant increase in sales revenue because of the following positions: grain, oilseed, and feed, products and services for farming, and food products, as explained by note 4 of the annual report (Linas Agro Annual Report 2021/2022). Another important element for analysis is X3, although it has the lowest weight in

Z-Score accrual-based model, it influences the general picture. This element consists of earnings before interest and taxes (EBIT) withdrawn from the income statement, divided by total assets from the balance sheet. Figure 4 assists in the analysis of this variable. Figure 4 shows fluctuations in the years 2018, 2019, and 2020 as well as a tremendous increase in the years 2021 and 2022. In the year 2018, EBIT declined slightly compared to the previous year due to the decrease in the value of biological assets and the lower value of the future crop harvest in the group-controlled agricultural companies (Linas Agro Interitm Report, 2017/2018).

Figure 4. The X3 variable trend



Source: author's calculations based on Appendix 1

As visible from Figure 4, the X3 variable has a negative value for the year 2019 due to the drop of EBIT to a negative amount (Linas Agro Interim Report, 2018/2019), and it was the only variable from all Z-Score calculations, which shown negative result. However, Figure 2 shows that in the year 2019 the company had the highest amount of current liabilities. It is visible from the income statement that EBIT is negative and visible from the calculation of X3 for the year 2019 that the value is negative. This correlation of facts means that the company has a negative EBIT and had to take additional loans to cover the expenses and losses. The managerial report states that Linas Agro decreased the face value of their debts, but has Group's financial expenses increased, meaning that the interest on loans has increased (Linas Agro Interim Report, 2018/2019). In the years 2020, 2021, and 2022 EBIT has grown again (Linas Agro Interim Report, 2019/2020, 2020/2021, 2021/2022), and X3 in Figure 4 reflects it. It is important to note that the variables X1, X2, and X4 consist of elements from the balance sheet, while the variables X3 and X5 contain elements not only from the balance sheet but also from the income statement (EBIT).

The rest of the variables X2 and X4 have not been changing drastically throughout the years of the research. Although X4 decreased from the year 2016 until the year 2020, in the year 2021, the variable increased, and in 2022, it has fallen down. In the years 2016–2020, there was an insignificant decrease in the market capitalization of the company, while there was a market capitalization growth in the years 2021–2022. In the year, 2022 X4 was 0.268, which was lower than in 2021 (0.609), although the market capitalization of the company has increased to EUR 158,940 thousand which is the highest capitalization Linas Agro ever had for the seven years of research. The reason for that in the year 2022 there is not only the highest market capitalization for the seven years of research but also a tremendous growth of total liabilities (over 100% compared to the previous year) which is the highest value for all researched years as well. Therefore, the primary reason for the decline in X4 variable in the year 2022 compared to 2021 is a tremendous increase in total liabilities, exceeding the growth of market capitalization. Figure 1 shows that Altman's Z-Score credit risk model places Linas Agro Group in the upper grey zone for the years 2016–2020, and in the green zone during the years 2021–2022, which means that according to this model, the company has no problems with solvency and liquidity. Because accrual-based credit risk models are widely used by financial institutions, this allows the company continuously increase its debt based on accrual-based credit risk model calculations. Since the analysis is based on the cash-flow principle, the relevant values were taken from cash-flow statements from the year 2016 until the year 2022. Data on total debts were taken from balance sheets. Table 4 below shows the template of Jury (2012), which was reworked and improved; it includes the analysis for the seven years. Calculation details are available in Appendix 1. The main element, which allows making a conclusion about the company's ability to repay the debt, is the number of years to repay debt, which is shown in the last line of Table 4. Table 2 provides the description and categorization of the outputs gained from the Jury's template. It is visible that according to the cash-based credit risk model calculations in Table 4, the number of years to repay for the years 2016-2018, 2022 is calculated as "never".

In the year 2019, the number of years to repay got to 41.48, and in 2020, it finally dropped to 4.77, and to 2.37 in the year 2021, the interpretations of the results are provided further in the paper. More explicit analysis of the results and the evidence of managerial manipulations investigated through the cash-based credit risk model is provided in the previous publication of the author (Litvinenko & Alver, 2023). It is important to mention that there is such a phenomenon as the debt-to-equity hypothesis when managers can shift the income from the future periods to the present because this decreases the debt-to-equity ratio (Hendriksen & Van Breda, 1992).

Table 4. Cash-based analysis based on Jury's template

Elements, in thousands of EUR	2016	2017	2018	2019	2020	2021	2022
Cash generated from operations	17,372	20,603	20,606	4,985	19,770	25,601	122,710
Changes in working capital	-	-	-	-	-	-	-
(Increase) decrease in biological assets	3,096	1,061	2,894	-968	3,508	1,032	-2,181
Decrease (increase) in inventories, incl. right of return asset	-15,098	1,511	-22,191	4,180	8,224	-2,657	-53,074
Decrease (increase) in prepayments	2,147	-553	-1,598	5,281	1,555	-1,805	1,316
Decrease in trade and other accounts receivable	4,057	-13,366	-15,790	3,201	5,614	2,708	-49,552
(Increase) in restricted cash	-449	199	-710	600	211	-374	343
Increase in trade and other accounts payable	13,020	-2,444	-1,401	3,500	164	20,070	-18,311
(Invested in)/ Generated from Net Working Assets	6,773	-13,592	-38,796	15,794	19,276	18,974	-121,459
Net Capex	-11,911	-15,707	-18,356	-11,440	-5,118	-6,249	-6,985
Cash Taxes	-1,251	-1,037	-1,824	-471	-165	-1,329	-7,128
Cash available to satisfy capital providers	-6,389	-9,733	-58,976	8,868	33,763	55,971	-134,321
Net interest	-1,896	-2,004	-2,074	-2,309	-2,337	-2,795	-12,778
Net dividends	-1,217	-1,228	-1,216	-2,939	-7	-12	-94
Cash available for debt service	-9,502	-12,965	-62,266	3,620	31,419	53,164	-147,193
Total net (debt)/cash	-98,492	-112,497	-153,968	-150,165	-149,895	-127,020	-298,085
Number of years to repay the debt	Never	Never	Never	41.48	4.77	2.37	Never

Note. Source: calculations based on the reworked template; Appendix 1

Further, the author proceeds with the comparative analysis of the results of the two credit risk models: accrual-based Altman Z-Score and cash-based Timothy Jury modified by the author. As visible from Table 5, the results gained from the accrual-based Atman Z-Score model are completely different from the cash-based Jury's credit risk model.

Table 5. Comparative analysis of accrual-based and cash-based credit risk models

Indicators	2016	2017	2018	2019	2020	2021	2022
Accrual-based credit risk model result	2.89	2.88	2.54	2.62	2.52	3.37	3.22
Altman Z-Score color classification	grey	grey	grey	grey	grey	green	green
Cash-based credit risk model result	never	never	never	41.48	4.77	2.39	never
Jury's template color classification	red	red	red	red to grey	green	green	Red

Note. Source: author's calculations based on Appendices 1 and 2

It is evident from Table 5 that during all the research years from 2016 until 2020 the company was in the upper grey zone and in the years 2021 and 2022 was in the green zone, according to Altman's Z-Score model. This model did not show any important changes in the financial strategy and situation of the company, which allowed Linas Agro to increase the total debt to the maximum level for the seven years of research.

Some studies confirm that the Z-Score model performs well (Altman et al., 2017). However, the cash-based credit risk model shows a completely different picture. It shows the dramatic fluctuations and changes in the company's financial situation and strategy. In the years 2016 to 2018 and in the year 2022, Linas Agro Group was in the red zone with a high probability of default and inability to repay the debt ("never"), according to the cash-based credit risk model. The company had enough profit but not enough cash to satisfy the debt providers to cover the debts. The only opportunity for the company to repay the debt was to increase the total debts repeatedly. Of course, the negative values of cash flow from operations can be disregarded, as well as the number of years to repay the debt classified as "never" if the company would have managed to perform the payouts with its funds, such as:

- increase equity through the attraction of external investors;
- increase its capital;
- sell out the inventory and non-current assets;
- increase sales;
- increase the profitability of company's operations;
- decrease manufacturing costs.

Let us take a closer look at the years 2016–2019 (the year 2022 will be reviewed separately). The financial strategy of the company was to continue increasing the total debts and continuing to pay out dividends to its stakeholders from the years 2016–2019. As stated by Hendriksen and Van Breda (1992), the dividend decision must take into consideration many factors such as capital growth and expansion objectives of the firm, external funding policies, and most importantly the availability of cash (Hendriksen & Van Breda, 1992). The strategy of Linas Agro goes against the researcher's findings.

Linas Agro started a transformation in the organizational structure in the year 2019, which allowed the company to reach the "red to grey" level with the mark of 41.48 years to repay the debt. The transformation included reducing operating costs, closure of the dormant company in Latvia, closure of Denmark company Linas Agro, implementing other programs increasing the efficiency of internal processes, and reducing operational costs (Linas Agro Interim Report, 2018/2019).

In the year 2020, significant changes in the company's strategy and management have happened. A new financial director replaced in 2020 the financial director, who was running the company until the year 2019 (Linas Agro Annual Report, 2019/2020). In addition, the auditor was changed in the year 2020 for KPMG, replacing the Ernst & Young auditing until 2019. Moreover, the company has changed its organizational structure and formed a sub-group of companies from new and acquired land management companies (Ibid.).

In the year 2020, the company changed its strategy (Linas Agro Interim Report, 2019/2020), which allowed it to

- decrease the amount of total debt, as calculated by the author in Appendix 3 and supported by the managerial report;
- get the positive value of the cash generated from the net working assets, as calculated in Appendix 2 and confirmed by the managerial report;
- get the positive result of net cash from operating activities as visible from the cash flow statement (Linas Agro Annual Report, 2019/2020);
- reach the green zone according to the cash-based credit risk model with a significant number of 4.77 (years to repay the debt), as calculated by the author in Appendix 2.

This speaks of the fact that in the company the management team restructuring has happened and the correct financial strategy was pursued. In the year 2021, the company continued to use the strategy of decreasing debt and increasing the positive cash from operations, which allowed the company to reach the green zone of the cash-based credit risk model with a score of 2.39 and to reach the green zone of the Z-Score accrual-based credit risk model with the score of 3.37. This is the first case when the models' results agree.

In the year 2022, the company got back the strategy of the debt increase. Thus, the debt increased by a significant amount, and the cash accumulated from the main operations was spent. This led to a situation, which has never happened for the previous seven years of research. Based on the Z-Score model the company reached a 3.22 score and the green zone classified as a mature company with low credit risk. However, the cash flow-based credit risk model shows that the company gets into the red category with the number of years to repay the debt classified as “never”. Thus, there are opposite results in the accrual-based and cash-based approaches. These results crown the seven years of research. Further analysis is described below based on the managerial and annual reports of the company. Based on the balance sheet data, the company has increased its non-current liabilities from EUR 50,057 thousand in the year 2021 to the amount of EUR 66,936 thousand in the year 2022. Nevertheless, current liabilities have increased from the amount EUR 174,865 thousand to EUR 526,088 thousand. The main items of the current liabilities, which have significantly grown, were current borrowing, which increased from EUR 63,000 thousand in the year 2021 to EUR 213,550 thousand in the year 2022; and also trade payables which increased from EUR 63,707 thousand in the year 2021 to EUR 205,687 thousand in the year 2022. Also, based on the annual report, “On 22 July 2022, AB Linas Agro concluded a syndicated credit agreement with Credit Suisse AG, Swedbank AB and AB SEB Bankas for the amount of EUR 170,000 thousand” (Linas Agro Annual Report, 2021/2022, 83). Linas Agro Group’s financial portfolio in the financial year 2021/2022 was EUR 296 million (Linas Agro Annual Report, 2021/2022, 20). While the main part of the working capital and long-term investments are financed by the following financial institutions: Swedbank AB, AB SEB bankas, Luminor Bank AS, Credit Suisse AG, Credit Europe Bank N.V. (Ibid.). According to the Annual Report 2021/2022 (Linas Agro Group Annual Report, 2021/2022, 64), Linas Agro Group has not fulfilled part of covenants under credit agreements for the following banks: Swedbank AS, Luminor AB, and SEB AB. The borrowings amounted to EUR 42,290 thousand and were recorded as short-term liabilities. In addition, Linas Agro Group and its subsidiaries have not fulfilled the short-term covenants in the total amount of EUR 9,227 thousand to OP Corporate Bank plc (Ibid.). In the year 2022, the cash-flow based credit risk model has shown negative results for Linas Agro Group with the increased possibility of credit risk defaults. The negative values are represented in the calculations above and are supported by the annual report, “Group’s cash flow from operating activities before the changes in the working capital was positive and amounted to EUR 123 million as compared to EUR 25 million of the corresponding period of the previous year. Cash flow from operating activities after changes in working capital was negative and amounted to EUR 6 million (positive EUR 43 million over the respective period of 2020/2021 financial year), the main reason for that being an increase in inventory (by EUR 155 million) and account receivables (by EUR 200 million)” (Linas Agro Group Annual Report, 2021/2022, p. 20). Based on the financial statements, it is clear that Linas Agro Group is mostly financed by short-term loans rather than long-term loans. Due to the fact that the company did not fulfil its long-term obligations, it enforced short-term credit agreements.

It is important to mention that the new auditor KPMG that audited the financial statements of Linas Agro Group for the financial year 2019/2020 has identified a significant increase in credit risk or credit-impaired (defaulted) exposures (Linas Agro Annual Report, 2019/2020). In addition, the auditor report in the annual report 2021/2022 stipulates that (Linas Agro Group Annual Report, 2021/2022)

- the assumptions used to estimate the credit risk of the related exposure and the client's expected future cash flows;
- identification of exposures with significant credit risk or credit impairment (default) - the assumptions used to estimate the credit risk of the related exposure and the client's expected future cash flows;
- identification of exposures with significant credit risk or credit impairment (default).

Auditor’s report underlines the importance of cash flows for the determination of the default. This was a residual result of previous years’ company policy. As a result of the calculations, there is a visible necessity to calculate the probability of default not only according to the accrual-based credit risk model, which is widely used nowadays in financial institutions but also to investigate the opportunity to use the cash-based credit risk models. Comparison of the results between these two models is highly appreciated to find the best suitable model for each particular case.

5. The effect of covid-19 and the war in Ukraine

Based on the company’s annual and management reports, Covid19 and the war in Ukraine negatively affected the research of the last two years 2020/2021 and 2021/2022. The main elements affected during these years are described below. The poultry business was highly affected by Covid-19. As the CEO of Linas Agro Group admitted in the annual report, Covid-19 made the poultry business unprofitable in the financial year 2020/2021 due to the induced labor shortages leading to production and delivery delays and in the year 2021/2022 the increase in energy prices placed the poultry farming business into a difficult position (Linas Agro Group Annual Report, 2021/2022,p. 17). In addition, according to the annual report, the amount of grants for poultry activity, related to Covid-19 in the year 2021 is EUR 962 thousand and EUR 3,722 thousand in the year 2022 (Ibid., p. 68). Another risk affecting the performance of Linas Agro Group was the political risk of war in Ukraine. Since Linas Agro Group is tight within its supply chain with Russian, Belarus, and Ukrainian partners, the war has led to disruptions in the supply chain, restrictions on payment systems, shortage of some products, and an increase in prices (Linas Agro Group Annual Report, 2021/2022, p. 51). Linas Agro Group reported several subsidiaries registered in Russia, Belarus, and Ukraine and controlled by Group. The

Sales revenues to customers from Russia for the year ended 30.06.2022 were EUR 117,522 thousand, and to the customers from Belarus were EUR 26,235 thousand (Ibid., p. 32). Thus, it is visible how Covid19 and the war in Ukraine negatively affected the company's financial position with a decrease in sales and an increase in costs.

6. Conclusions

The analysis presented in this study contributed both to the theoretical knowledge base about credit risk analysis, as well as it served the benefits of financial practitioners showing that cash-based credit risk analysis possesses a variety of benefits, and can provide precise analysis alone or in combination with accrual-based credit risk model. The present study with the credit risk analysis is based on IFRS principles analyzing the financial statements for the last seven years of the company listed on the stock exchange.

As a result of the research, the author of this paper answered the research questions:

1. What are the potential strengths of the credit risk model based on the cash flow principle?

   As revealed by the implementation of the cash-based credit risk model, its strengths are:
   - Visibility of the actual financial situation of the company, its ability to cover the debt and specifying the source of debt coverage.
   - It is more difficult to manipulate data in the cash flow statement compared to accrual-based statements, especially in the section of cash flows from operating activities.
   - It shows more clearly whether the company is close to bankruptcy and specifies the probability of default.
2. What are the weaknesses of the accrual-based credit risk model?

   Weaknesses of the accrual-based credit risk model were revealed during implementation and comparison with the cash-based model. Weaknesses are as follows:
   - This model showed no significant changes in the company's financial situation for all research periods.
   - The model has shown the company to be in the grey zone in the first five years (2016–2020) and in the green zone in the last two years of the study (2021–2022), both classified as creditworthy.
   - The model allowed the company to continue increasing its debts and getting deeper into the debt trap striving for bankruptcy.
3. What are the benefits of the combined use of both cash-based and accrual-based credit risk modeling methods when analyzing companies? The benefits are:
   - A clearer vision of the company's financial situation.
   - Better prediction of the probability of bankruptcy, credit risk, and default.

- More balanced and justified decisions for financial institutions when issuing loans.

The present research shows that Altman's Z-Score credit risk model based on the analysis of traditional accrual-based financial statements works well if the financial managers of the analysed entities did not manipulate the data. On the other hand, the actual results can be hidden well by financial managers if they possess the skills to manipulate accrual-based financial statements. In this case, accrual-based credit risk models cannot recognize the pre-bankruptcy state of the analysed company and assign a misleading moderate result. With cash-based credit risk models, the situation is different because they are less prone to manipulations from the side of financial managers because the vast majority do not have enough knowledge on how to manipulate the statement of cash flows. Therefore, the novelty of the present research is in theoretical and practical-based evidence developed through the comparison of the credit risk analysis methods and their application to the case of the production company. It prepares significant theoretical grounds for the development of the credit risk models surpassing the existing ones with the preciseness of analysis, estimation of the pre-bankruptcy state of the company and visibility of possible manipulations of the parties concerned.

As it becomes evident from this research, it is important for the financial analysis and audit to reveal the actual financial situation of the companies to estimate the probability of default and predict bankruptcy. It is important to admit, that the only financial structure which indicated the company's actual financial situation and reacted properly, was the stock exchange. The fluctuation of *Linas Agro Group* share prices was the evidence (Nasdaq Baltic, 2021). Traders perform the analysis of the company's solvency, liquidity, and profitability, as well as forecasting using not only accrual-based tools but relying on cash-based tools a lot (Ramnath et al., 2006). However, sometimes traders are overly optimistic. Studies have shown that even when a company has filed for bankruptcy an increase in share price can happen when large traders create bull market conditions due to the optimistic spirit of investors (Panigrahi, 2019). The threat of insolvency of the company felt by stockholders causes equity and credit markets to react with a decrease in shares price and the loss of value of the certificates of indebtedness (Hendriksen & Van Breda, 1992). This in its turn increases the costs of additional borrowing for the company, complicates the growth, and attempts to overcome financial difficulties.

The future research of the author is dedicated to building a new credit risk model consisting of the combination of accrual-based and cash-based ratio indexes with some macroeconomic elements as well as elements of forecasting based on multiple linear regression methods.

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APPENDICES

Appendix 1. Author's calculations of the Z-Score credit risk model for 7 years

30.06.2016	Calculation, thousands of EUR	Result
X1	59,229 / 332,473	0.178
X2	88,310 / 332,473	0.266
X3	7198 / 332,473	0.022
X4	106,490 / 170,512	0.625
X5	615,959 / 332,473	1.853
Z	(1.2×0.178)+(1.4×0.266)+(3.3×0.22)+(0.6×0.625)+(0.999×1.853)	2.885
30.06.2017	**Calculation, thousands of EUR**	**Result**
X1	65,312 / 352,849	0.185
X2	95,177/352,849	0.267
X3	12,054 / 352,849	0.034
X4	104,900 / 183,632	0.571
X5	644,952 / 352,849	1.828
Z	(1.2×0.185)+ (1.4×1.267)+(3.3×0.034)+(0.6×0.571)+(0.999×1.828)	2.876
30.06.2018	**Calculation, thousands of EUR**	**Result**
X1	71,899 / 400,937	0.179
X2	102,951 / 400,937	0.257
X3	9597 / 400,937	0.024
X4	114,437 / 223,863	0.511
X5	634,423 / 400 937	1.582
Z	(1.2×0.179)+(1.4×0.257)+(3.3×0.024)+(0.6×0.511)+(0.999×1.582)	2.541
30.06.2019	**Calculation, thousands of EUR**	**Result**
X1	50,505 / 391,398	0.129
X2	89,955 / 391,398	0.23
X3	-3336 / 391,398	-0.085
X4	100,132 / 221,328	0.452
X5	742,542 / 391,398	1.897
Z	(1.2×0.129)+(1.4×0.23)+(3.3×-0.085)+(0.6×0.452)+(0.999×1.897)	2.615

Appendix 1 (continued 1)

30.06.2020	**Calculation, thousands of EUR**	**Result**
X1	55,642 / 405,421	0.137
X2	105,122 / 405,421	0.259
X3	14,827 / 405,421	0.037
X4	93,775 / 224,219	0.412
X5	657,700 / 405,421	1.622
Z	(1.2×0.137)+(1.4×0.259)+(3.3×0.037)+(0.6×0.412)+(0.999×1.622)	2.516
30.06.2021	**Calculation, thousands of EUR**	**Result**
X1	76,787/421,123	0.182
X2	119,333/421,123	0.283
X3	19,952/421,123	0.046
X4	136,991/224,902	0.609
X5	942,442/421,123	2.238
Z	(1.2*0.182)+(1.4*0.283)+(3.3*0.046)+(0.6*0.609)+(0.999*2.238)	3.365

30.06.2022	**Calculation, thousands of EUR**	**Result**
X1	129,501/872,975	0.148
X2	197,383/872,975	0.226
X3	103,619/872,975	0.119
X4	158,940/593,024	0.268
X5	1,895,667/872,975	2.171
Z	(1.2*0.148)+(1.4*0.226)+(3.3*0.119)+(0.6*0.268)+(0.999*2.171)	3.217

Appendix 2. Author's calculations of cash-based credit risk model

In thousands of EUR	2022	2021	2020	2019	2018	2017	2016
Cash generated from operations	122,710	25,601	19,770	4,985	20,606	20,603	17,372
Changes in working capital	–	–	–	–	–	–	–
(Increase) decrease in biological assets	-2,181	1,032	3,508	-968	2,894	1,061	3,096
Decrease (increase) in inventories, incl. right of return asset	-53,074	-2,657	8,224	4,180	-22,191	1,511	-15,098
Decrease (increase) in prepayments	1,316	-1,805	1,555	5,281	-1,598	-553	2,147
Decrease in trade and other accounts receivable	-49,552	2,708	5,614	3,201	-15,790	-13,366	4,057
(Increase) in restricted cash	343	-374	211	600	-710	199	-449
Increase in trade and other accounts payable	-18,311	20,070	164	3,500	-1,401	-2,444	13,020
(Invested in)/ Generated from Net Working Assets	-121,459	18,974	19,276	15,794	-38,796	-13,592	6,773
Net Capex	-6,985	-6,249	-5,118	-11,440	-18,356	-15,707	-11,911
Cash Taxes	-7,128	-1,329	-165	-471	-1824	-1,037	-1,251
Cash available to satisfy capital providers	-134,321	55,971	33,763	8,868	-58,976	-9,733	-6,389
Net interest	2,293 - 15,071 = -12,778	756 - 3,551 = -2,795	817 - 3,148 = -2,337	635 - 2,944 = -2,309	503 - 2577 = -2074	868 - 2,872 = -2004	273 - 2,169 = - 1,896
Net dividends	0 - 94 = -94	0 - 12 = -12	1 - 8 = -7	4 - (17+2,926) = -2,939	14+1,202 = -1,216	26+1202 = -1,228	15+1,202 = -1,217
Cash available for debt service	-147,193	53,164	31,419	3,620	-62,266	-12,965	-9,502
Total net debt (-) in cash	-298,085	-127,020	-149,895	-150,165	-153,968	-112,497	-98,492
Number of years to repay	NEVER	2.39	4.77	41.48	NEVER	NEVER	NEVER

Notes:
1. Cash Generated from Operations 2022 = -5,877 + 7,128 - 122,710 = - 121,459
2. Cash Generated from Operations 2021 = 43,121 + 1,329 - 25,476 = 18,974
3. Cash Generated from Operations 2020 = 38,881 + 165 - 19,276 = 19,770
4. Cash Generated from Operations 2019 = 20,308 + 471 - 15,794 = 4,985
5. Cash Generated from Operations 2018 = -20,014 + 1,824 + 38,796 = 20,606

6. Cash Generated from Operations 2017 = 5,974 + 1,037 + 13,592 = 20,603
7. Cash Generated from Operations 2016 = 22,894 + 1251 - 6,773 = 17,372

Appendix 3. Authors' total debt calculations

Year 2022. Total Net (Debt) in Cash	2022
Net debt at beginning of the year	127,020
Increase in cash in the year	2,803
Decrease in short-term borrowing	150,435
Current portion of long-term borrowing	3,522
Decrease in long-term borrowing	9,249
Finance lease obligation (non-current)	4,719
Current portion of finance lease obligations	2,106
Deferred income tax liability	1,034
Change in net debt	171,065
Total net (debt)/cash	298,085

Year 2022. Total Net (Debt) in Cash	Beginning	Ending	Difference
Cash	18,007	20,810	2,803
Short-term borrowing	63,115	213,550	150,435
Current portion of long-term borrowing	17,119	20,641	3,522
Long-term borrowing	13,056	22,305	9,249
Finance lease obligation (non-current)	27,148	31,867	4,719
Current portion of finance lease obligations	5,553	7,659	2,106
Deferred income tax liability	1,029	2,063	1,034
Total (debt)/cash	127,020	298,085	171,065
Difference	0	0	0
Total net (debt) / cash	127,020	298,085	171,065

Year 2021. Total Net (Debt) in Cash	Changes
Net debt at beginning of the year	149,874
Increase in cash in the year	8,468
Decrease in short-term borrowing	29,614
Current portion of long-term borrowing	3,989
Decrease in long-term borrowing	5,636
Finance lease obligation (non-current)	7,670
Current portion of finance lease obligations	561
Deferred income tax liability	1,760
Change in net debt	22,854
Total net (debt)/cash	127,020

Appendix 3 (continued 1)

Year 2021. Total Net (Debt) in Cash	Beginning	Ending	Difference
Cash	9,539	18,007	8,468
Short-term borrowing	92,729	63,115	29,614
Current portion of long-term borrowing	13,130	17,119	3,989
Long-term borrowing	18,692	13,056	5,636
Finance lease obligation (non-current)	19,478	27,148	7,670
Current portion of finance lease obligations	4,992	5,553	561
Deferred income tax liability	853	1,029	176
Total (debt)/cash	111,421	76,171	35,250
Difference	38,453	50,849	12,396
Total net (debt) / cash	149,874	127,020	22,854

Year 2020: Total Net Debt (-) in Cash. Changes	Changes
Net debt at beginning of the year	150,165
Increase in cash in the year	1,902
Decrease in short-term borrowing	20,810
Current portion of long-term borrowing	281
Decrease in long-term borrowing	1,101
Finance lease obligation (non-current)	-17,040
Current portion of finance lease obligations	-4,117
Deferred income tax liability	-761
Change in net debt	270
Total net (debt)/cash	149,895

Year 2020. Total Net Debt (-) in Cash	Beginning	Ending	Difference
Cash	7,637	9,539	1,902
Short-term borrowing	113,539	92,729	20,810
Current portion of long-term borrowing	13,411	13,130	281
Long-term borrowing	19,793	18,692	1,101
Finance lease obligation (non-current)	2,455	19,495	17,040
Current portion of finance lease obligations	875	4,992	4,117
Deferred income tax liability	92	853	761
Total (debt)/cash	146,743	124,551	22,192
Difference	3,422	25,344	21,922
Total net (debt) / cash	150,165	149,895	270

Appendix 3 (continued 2)

Year 2019: Total Net Debt (-) in Cash. Changes	Changes
Net debt at beginning of the year	153,965
Increase in cash in the year	-2,858
Decrease in short-term borrowing	4,570
Current portion of long-term borrowing	-6,576
Decrease in long-term borrowing	7,387
Finance lease obligation (non-current)	-1,283
Current portion of finance lease obligations	-316
Deferred income tax liability	18
Change in net debt	3,800
Total net (debt)/cash	150,165

Year 2019: Total Net Debt (-) in Cash	Beginning	Ending	Difference
Cash	10,495	7,637	2,858
Short-term borrowing	118,109	113,539	4,570
Current portion of long-term borrowing	6,835	13,411	6,576
Long-term borrowing	27,180	19,793	7,387
Finance lease obligation (non-current)	1,172	2,455	1,283
Current portion of finance lease obligations	559	875	316
Deferred income tax liability	110	92	18
Total (debt)/cash	145,399	146,743	1344
Difference	8,566	3,422	5,144
Total net (debt) / cash	153,965	150,165	3,800

Year 2018. Total Net Debt (-) in Cash. Changes	Changes
Net debt at beginning of the year	112,497
Increase in cash in the year	1,598
Decrease in short-term borrowing	-40,615
Current portion of long-term borrowing	4,226
Decrease in long-term borrowing	-6,779
Finance lease obligation (non-current)	-96
Current portion of finance lease obligations	0
Deferred income tax liability	-739
Change in net debt	-41,468
Total net (debt)/cash	153,968

Appendix 3 (continued 3)

Year 2018. Total Net Debt (-) in Cash	Beginning	Ending	Difference
Cash	8,897	10,495	1,598
Short-term borrowing	77,494	118,109	40,615
Current portion of long-term borrowing	11,061	6,835	4,226
Long-term borrowing	20,401	27,180	6,779
Finance lease obligation (non-current)	1,076	1,172	96
Current portion of finance lease obligations	559	559	0
Deferred income tax liability	1,906	110	1,796
Total (debt)/cash	98,971	145,399	22,192
Difference	13,256	8,566	21,922
Total net (debt) / cash	112,497	153,965	41,468

Year 2017: Total Net Debt (-) in Cash. Changes	Changes
Net debt at beginning of the year	98,492
Increase in cash in the year	1,996
Decrease in short-term borrowing	-19,402
Current portion of long-term borrowing	8,882
Decrease in long-term borrowing	-3,660
Finance lease obligation (non-current)	152
Current portion of finance lease obligations	374
Deferred income tax liability	-351
Change in net debt	-14,005
Total net (debt)/cash	112,497

Year 2017: Total Net Debt (-) in Cash	Beginning	Ending	Difference
Cash	6,901	8,897	1,996
Short-term borrowing	58,092	77,494	19,402
Current portion of long-term borrowing	19,943	11,061	8,882
Long-term borrowing	16,741	20,401	3,660
Finance lease obligation (non-current)	1,228	1,076	152
Current portion of finance lease obligations	933	559	374
Deferred income tax liability	1,555	1,906	351
Total (debt)/cash	76,388	98,971	22,583
Difference	22,104	13,256	8,848
Total net (debt) / cash	98,492	112,497	14,005

Appendix 3 (continued 4)

Year 2016: Total Net Debt (-) in Cash. Changes	Changes
Net debt at beginning of the year	104,047
Increase in cash in the year	221
Decrease in short-term borrowing	6,164
Current portion of long-term borrowing	-6,630
Decrease in long-term borrowing	5,988
Finance lease obligation (non-current)	561
Current portion of finance lease obligations	-130
Deferred income tax liability	-398
Change in net debt	5,555
Total net (debt)/cash	98,492

2016 Year: Total Net Debt (-) in Cash	Beginning	Ending	Difference
Cash	6,680	6,901	221
Short-term borrowing	64,256	58,092	6,164
Current portion of long-term borrowing	13,313	19,943	6,630
Long-term borrowing	22,729	16,741	5,988
Finance lease obligation (non-current)	1,789	1,228	561
Current portion of finance lease obligations	803	933	-130
Deferred income tax liability	1,157	1,555	-398
Total (debt)/cash	88,774	76,388	12,386
Difference	15,273	22,014	6,741
Total net (debt) / cash	104,047	98,492	5,555