New Approaches to Financial and Bankruptcy Risk

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Abstract. *A consistent direction in which financial risk and bankruptcy analysis models were developed was the inclusion of artificial intelligence algorithms in the methodology, they are being used in most of the cases to achieve some classifications. The artificial intelligence (machine learning) algorithms widely used for the analysis of financial or bankruptcy risks, presented in the paper, are: KNN (K-Nearest Neighbor) algorithm; Support Vector Machine (SVM); Random Forest; Neural networks (ANN – Artificial Neural Networks). Using these algorithms, companies can be classified into different categories, based on some variables, and the final result is to obtain a certain probability of bankruptcy or insolvency for that company. Obviously, there are limitations of the models and problems that can arise from their estimation, among the most well-known being overfitting (the risk of learning the model to perform very well only for the data series being used on). In recent years, ESG (Environmental, Social and Governance) factors have played a very important role. We believe that this is a direction in which the analysis of bankruptcy risk and financial risks could go, by including sustainability aspects in the models*

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1. Introduction

Financial and bankruptcy risks are intensively analyzed and debated in the specialized literature, with a large number of researches and articles being carried out in this area. There are a number of methods and methodologies that allow their analysis and the drawing of conclusions, these can be from the simple ones, based on financial analysis indicators, to the most complex ones, which are based on probabilistic models, as Chen and Tseng did (2012) or Thomson and Graham (1996) in their papers. The specialized literature is very rich in terms of this type of analysis, and the conclusions were among the most diverse, drawn for different industries and for different geographical areas.

Analysis methods in terms of financial and bankruptcy risk have developed over time, with more approaches emerging that take into account more and more elements. A direction in which financial risk and bankruptcy analysis models were developed was the inclusion of artificial intelligence algorithms in the methodology.

2. Scientific literature

There are numerous works in the foreign literature that have applied artificial intelligence algorithms to bring up a new approach to financial and bankruptcy risk in companies. The most useful papers that were examined were by Leo, Sharma, and Maddulety (2019), Kim, Cho, and Ryu (2020), and Moscatelli, Parlapiano, Narizzano, Viggiano (2020). In these articles, the authors highlighted the usefulness of the methodology within the machine learning algorithms to make predictions regarding the bankruptcy of the companies that were the focus of the analysis. The work methodology involved the estimation of probabilities using algorithms for the classification and ranking of these companies according to the risk they carry. The results indicated that the models can be successfully used to solve such a problem related to corporate finance, but also to credit risk, and they can be successfully applied within a banking risk policy related to risk modelling. In this sense, we even noticed a tendency, still incipient at the level of banking groups in Romania, to focus on the recruitment of specialized staff in this direction to bring a new approach to the level of the credit risk department.

Among the classic but current methodologies that give a new approach to the problem of measuring bankruptcy risk and financial risks is the one based on the estimation of logistic models, in different forms. Here we can talk about logit or probit models, and the results can be comparable to what can be obtained by applying some machine learning algorithms, both in terms of the performance of the built model and in terms of efficiency and ease of implementation. After going through several works in the specialized literature, we identified that there are numerous articles that addressed this methodology, both for the Romanian market and for foreign markets. Among the works that focused on the Romanian market, we consider it worth mentioning the one published by Smaranda (2014) and the one published by Istrate and Ionescu (2017), through which they applied logistic regressions in order to reach certain conclusions regarding the risk of companies going bankrupt, using a series of parameters established on the basis of economic intuition, but also on the basis of specialized literature research. The results were good, contributing to a classification and ranking, a fact that can form a certain perspective regarding a certain sector in Romania.

As already stated, this methodology has been widely used, it has also been applied by other authors abroad for the cases of local economies, providing additional security in terms of its validity and the fact that it is a perspective in terms of the direction in which the analysis of financial and bankruptcy risk at the level of firms could go. An important work is the one carried out by Kovacova and Kliestik (2017), through which they were able to successfully apply the logit and probit models to estimate the probability of bankruptcy for Slovak companies, the analysis method being the same as that applied to the companies of on the local market in the previously presented studies.

It is worth recalling, as a basis for a future case study, the article by the authors Vaclav and David (2017), in which they analysed, using the same methodology related to probit and logit models, the bankruptcy risk of companies in the European agricultural sector. It is also worth noting that the analysis focused on a sector that has been less analysed lately, not being very attractive for the media space, and this has decreased the interest in this area. On the other hand, this sector is a very important one, where the viability of the companies is a relevant aspect in the sense of ensuring food security in Europe, this is probably the main argument that should be the basis of substantiating a need for granting a high interest to the agricultural sector. At the same time, the analysis from the point of view that financial stability and the risk of bankruptcy could be used in an advisory sense by the participants in this sector, representing a direction to improve the financial statements of the companies, better preparing them in this way for accessing bank financing, from national funds, from European funds or perhaps even through the issue of bonds.

An analysis for the same sector was also carried out by the Romanians Aldea and Lădaru (2011) six years before, they even highlighted the need to develop bankruptcy risk analysis models for companies in the agricultural sector, emphasizing the fact that it is a sector with high specificity, a sector for which the existing models must be adapted to include specific risk factors, and here, in recent years, ESG (Environmental, Social and Governance) factors would play a very important role. This approach is increasingly present and there are many discussions at European level to increase the involvement in this area, many of the companies will be required to report and apply a series of measures to respond to the new regulations. From this area of European regulations regarding durability and sustainability factors (ESG), the most important is the European directive called CSRD (Corporate Sustainability Reporting Directive). This will apply to companies that meet certain size criteria, and they will also pass on the requirements to their customers and suppliers. Therefore, we believe that it is an element that should be taken into account in the future, more and more, when analyzing the risk of bankruptcy or financial risks, even if it comes from a non-financial area. This type of regulation and non-compliance can lead to direct (fines) or indirect losses, by reducing the number of customers or the refusal of some partners to work with a company that does not comply with this direction.

We have noticed that more and more researches have appeared in the specialized literature that take this direction into account and that have sought to quantify the impact on firm performance and the risk of bankruptcy. An important article for this type of discussion is written by Atif and Ali (2021), through which they sought to link the reporting that companies do regarding the ESG area to the risk of bankruptcy. The results obtained indicated a clear trend of increased bankruptcy risk for those that report very little in this area or for those that have an inappropriate measurement of sustainability risks (ESG). Another article that directly addresses this correlation is that of Aslan, Poppe, and Posch (2021). The three, in turn, reached conclusions validating the link between default risk and poor sustainability risk management (ESG) at the level of companies.

On the other hand, deficient reporting on ESG and poor management of these risks can manifest itself through an increase in financial risks at the company level, and the most important possible impact is on the cost of financing. An important paper that analyzed this relationship is that of the authors Raimo, Caragnano, Zito, Vitolla and Mariani (2021), who showed that firms that report extensively in the non-financial area (ESG) and that consider sustainability risks tend to be able to obtain financing at lower costs than other firms that do not.

3. The role of artificial intelligence algorithms in bankruptcy risk analysis

Artificial intelligence (machine learning) algorithms widely used for financial or bankruptcy risk analysis are the following:

a) K-Nearest Neighbor: this type of algorithm can be used for both classification and regression. For both situations, the input to this algorithm is the selection of the k closest training examples. For the regression case, the output variables are the eigenvalue for the current object, which is calculated as an average of the k nearest neighbors. When used for classification, the output variable is the class to which the example in the test set belongs. Such an example is classified based on the nearest neighbor majority vote. The KNN algorithm is a supervised learning algorithm that brings insight into the nature of the data, being very sensitive to its local structure;

b) Support Vector Machine (SVM): is a supervised learning algorithm classified under classification techniques. It is a binary classification technique that uses the training data set to predict an optimal hyperplane in an n-dimensional space. This hyperplane is used to classify new data sets. Being a binary classifier, the hyperplane divides the training data set into two classes. SVM algorithms are used to classify data in a two-dimensional plane as well as a multidimensional hyperplane. The multidimensional hyperplane uses "kernels" to classify multidimensional data;

c) Random Forest: "random forest" is one of the most popular tree-based supervised learning algorithms. It is also the most flexible and easy to use. The algorithm can be used to solve both classification and regression problems. Random forest tends to combine hundreds of decision trees and then trains each decision tree on a different sample of observations. The final predictions of the random forest are made by averaging the predictions of each individual tree. The benefits of random forests are numerous. Individual decision trees tend to overfit the training data, but random forest can mitigate this problem by averaging the predictions from different trees. This gives random forests higher predictive accuracy than a single decision tree. The random forest algorithm can also help to find important features in the data set. It is the basis of the Boruta algorithm, which selects important features from a data set";

d) Artificial Neural Networks (ANN): they are artificial structures that try to copy the way the human brain works and are built from several processing elements (EPs) or artificial neurons grouped in layers, each layer having a variable number of elements. In the most general way, each neuron can receive information from other neurons and/or even from itself (Floria, S. A., 2020, p. 16). From the point of view of classification problems, a neural network (RNA) gives rise - through its processing elements (neurons) - to discriminant functions. The topology of the artificial neural network and the value of the weights are the two factors that define and determine the number and way of coupling the discriminant functions.

Based on these algorithms, companies can be classified into different categories, based on some variables, and the final result is to obtain a certain probability of bankruptcy or insolvency for that company. Obviously, there are limitations of the models and problems that can arise from their estimation, among the most well-known being the risk of learning the model to work very well only for the data series for which the training is done (the risk of overfitting). Many of the machine learning models have this problem and for their recovery a good knowledge of the data series and their thorough preparation is necessary to avoid calibration problems.

4. Sustainability factors and their impact on bankruptcy risk

The area of sustainability factors (ESG) is increasingly regulated, with strong attention being drawn to it in recent years, and the tendency is to increase interest in these risks. It is widely accepted that sustainability factors affect firm performance and bankruptcy risk, but until now there has been no regulated and organized framework in terms of reporting in this area and in terms of how these factors can be quantified in order to analyze the impact on the risk of bankruptcy or other financial risks.

Thus, according to the new regulations, companies' reports will have to take into account a series of information related to environmental issues, social impact and corporate governance, which could be elements that would have an impact on the company's performance. Factors that can be considered are the following:

a) **environmental criteria –** these may include CO_2 (carbon dioxide) emissions and greenhouse gases, electricity consumption, selective waste recycling or combating various types of environmental risks, etc. Furthermore, the criteria may include the assessment of the environmental risks faced by the firms, but also how they manage them. These criteria are related to the quality and functioning of the environment and natural systems, which may have an impact on the activity of issuers and counterparties. The main transmission mechanisms for the impact of environmental factors are physical (such as weather events and gradually deteriorating climate conditions) and transition (such as restrictive regulations or additional taxes, disruptive technologies and changing consumer preferences) transmission channels. The impact of environmental factors can be twofold. The financial performance of an issuer or counterparty may be affected by environmental factors (for example, the introduction of a carbon tax may reduce the profitability of businesses dependent on them or reduce the competitiveness of their products).

b) **social criteria** - may include the quality of social dialogue within the company, the employment of people with disabilities, working conditions and employee training, the percentage of profit donated to local communities, relations with suppliers, etc.

They are generally related to the rights, welfare and interests of people and communities, which may impact on the activity of issuers and counterparties. Such factors as inequality, discrimination, lack of diversity, violation of labor rights or human rights can have a financial impact on companies that apply low standards in these respects, in the form of increased cost of compliance, compensation to be paid to affected parties in following lawsuits, fines, loss of market share as a result of reputational risk, etc., thus increasing the credit risk of the respective counterparty or issuer. Environmental factors and social factors are interconnected.

c) **corporate governance criteria** - may include the transparency of accounting methods and executive compensation, the fight against corruption and conflicts of interest, the number of women on boards of directors, etc. Many countries have implemented regulations regarding this level of equality. Thus, these criteria refer, in most cases, to the governance practices of issuers and counterparties, including the inclusion of ESG factors in their policies and procedures. Governance factors can lead to governance risks in many ways. For example, a weak code of conduct or lack of action in preventing and combating money laundering can adversely affect a company's resources, thereby affecting its potential to perform and generate revenue. Moreover, if such practices become public, customers and investors may lose confidence in the company, which may lead to penalties and legal costs, which in the long term may affect its ability to do business.

Governance plays a fundamental role in ensuring the integration of social and environmental considerations by a given issuer/counterparty. Recognizing the potential impact of climate and environmental change, physical, transition and liability risks is a sign of good governance.

At the same time, as the legislation expands in this area and as potential sanctions arise, these differences in financing costs can be increasingly high. Furthermore, all the risks of non-compliance with legislation and the lack of transparency regarding sustainability factors are and will be even more strongly translated into the financing costs of companies.

Considering all the arguments and research presented, we believe that this is a direction in which analyses of bankruptcy risk and financial risks could go, by including sustainability aspects in the models. All the more it can be a good direction to follow as most banks propose to consider aspects related to sustainability factors for their scoring models, and an analysis from companies could be extended in this area, to be able to have a clear and pertinent assessment of the risk factors to which the company is exposed.

5. Conclusions

The paper identifies the new analysis methods regarding financial and bankruptcy risks in the new context marked by the establishment of sustainable investment priorities, but also considering the development of the large-scale use of machine learning algorithms (artificial intelligence).

There are obviously ways the work could be improved. The area of bankruptcy risk analysis through classification algorithms (machine learning) can be a good direction to follow for the theoretical part, by presenting the different methodologies behind it and by including the results obtained by other authors. Furthermore, the state of knowledge can also be expanded by including more papers that could be used as a foundation for a future case study regarding new approaches to financial and bankruptcy risks. We refer to the area of integration of sustainability risks (ESG) in the impact analysis on the risks analyzed by the classical methods.

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