

A New Explorative Model to Assess the Financial Credit Risk Assessment

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Abstract—In recent years, Financial Credit Risk Assessment (FCRA) has become an increasingly important issue within the financial industry. Therefore, the search for features that can predict the credit risk of an organization has increased. Using multiple statistical techniques, a variance of features has been proposed. Applying a structured literature review, 238 papers have been selected. From the selected papers, 700 features have been identified. The features have been analyzed with respect to the type of feature, the information sources needed and the type of organization that applies the features. Based on the results of the analysis, the features have been plotted in the FCRA Model. The results show that most features focus on hard information from a transactional source, based on official information with a high latency. The main contribution of this paper is the FCRA Model combined with the plotted results, indicating multiple questions for further research.

Keywords—Financial Credit Risk Assessment; Business Failure Prediction; Credit Risk Features; DMN Requirements Diagrams (DRD).

I. INTRODUCTION

Within the field of the Financial Credit Risk Assessment (FCRA) there are two main areas of interest. Credit rating (or scoring) is used to solve the problem to label companies as bad/good credit or bankrupt/healthy. Credit rating is used not only internally for screening borrowers, pricing loans and managing credit risk thereafter, but also externally for calibrating regulatory capital requirements [1]. Bankruptcy (failure) prediction (or business failure prediction or going concern assessment) is intended to predict the probability that the company may belong to a high-risk group or may become bankrupt during the following year(s). Both of them are strongly related and solved in a similar way, namely as a binary classification task. In this paper, both categories of problems are collectively called Financial Credit Risk Assessment, which is a business decision-making problem that is relevant for creditors, auditors, senior management, bankers and other stakeholders.

Financial Credit Risk Assessment is a domain which has been studied for many decades. According to Balcaen and Ooghe [2], there are four main areas with reference to Financial Credit Risk Assessment: (1) Classical paradigm (arbitrary definition of failure, non-stationarity and data instability, sampling selectivity), (2) Neglect of the time dimension of failure (use of one single observation, fixed score output/concept of resemblance/descriptive nature, failure not seen as a process), (3) Application focus (variable selection, selection of modelling method), (4) Other

problems (use of a linear classification rule, use of annual account information, neglect of multidimensional nature of failure). The literature on Financial Credit Risk Assessment and business failure dates back to the 1930's [27]. Watson and Everett [3] described five categories to define failure: 1) ceasing to exist (discontinuance for any reason), 2) closing or a change in ownership, 3) filing for bankruptcy, 4) closing to limit losses and 5) failing to reach financial goals. When the Financial Credit Risk Assessment is negative, it is called business failure, which is a general term and, according to a widespread definition, it is the situation that a firm cannot pay lenders, preferred stock shareholders, suppliers, etc., or a bill is overdrawn, or the firm is bankrupt according to the law [4]. There is extensive literature in which this topic has been researched from the perspective of auditors or bankers. On the other hand, rare literature can be found about related literature from an information and decision perspective. The features (variables) which are relevant in the field of Financial Credit Risk Assessment will be analyzed in this paper. In this paper the focus will be on the auditor's, bankers and crediting rating firms, hence forward the term financial industry will be used to describe all three. A combination will be made between the financial industry and an information and decision perspective.

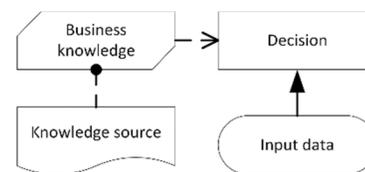


Figure 1. DRD-level elements

To do so, the DRD model will be used. The reason DMN is used is because it is currently the standard to model decisions. In September 2015, the Object Management Group (OMG) [5] released a new standard for modelling decisions and underlying business logic, DMN (Decision Model and Notation). The DMN standard is based on two levels; the Decision Requirements Diagram (DRD) level and the Decision Logic Level (DLL). The DRD level consists of four concepts that are used to capture essential information with regards to decisions: 1) the decision, 2) business knowledge, which represents the collection of business logic required to execute the decision, 3) input data, and 4) a knowledge source, which enforces how the decision should be taken by influencing the underlying business logic. The contents of the DLL are represented by the business knowledge container in the DRD level.

The remainder of this paper is organized as follows. Section II contains a description of relevant literature regarding features and feature selection with reference to Financial Credit Risk Assessment, from a combined perspective of both the financial industry and information and decision analysts, followed by the research method in Section III. In Section IV, our data collection and analysis will be reported. Subsequently, in Section V, a presentation of the results derived from the applied data analysis techniques will be given. The conclusion (Section VI) closes the article.

II. LITERATURE REVIEW

Feature selection is a critical step in Financial Credit Risk Assessment. Features (or variables or attributes) can be irrelevant, redundant or useful. There are several alternative methodologies for feature selection. Tsai [6] compares five well-known feature selection methods used in bankruptcy prediction, which are: 1) *t*-test, 2) correlation matrix, 3) stepwise regression, 4) Principle Component Analysis (PCA) and 5) factor analysis.

From a DMN perspective, a feature can either be a decision or an input data element. The choice between which element is used depends on one characteristic: derivation. Must the features be derived from other features then it is depicted as decision, for example expected market growth and, honesty in negotiation of human resources motivation. If the feature can be retrieved from a database or document, it is an input data element, for example retained earnings/total assets, or Total debt/total assets. Feature selection refers to the process that reduces the feature space and selects an optimum subset of relevant features. Three possible methods can be distinguished: human, statistical and hybrid. Statistically, there are two alternative approaches available. The first assesses the attributes in terms of measures independent of the learning algorithm that will be used. This is called the ‘filter’ approach. The second evaluates the subset according to the method that will ultimately be used for learning. This approach is called ‘wrapper’ [7]. There are two broad categories of techniques applied in Financial Credit Risk Assessment: statistical techniques and the (state-of-the-art) intelligent techniques. In the earliest research on Financial Credit Risk Assessment (FitzPatrick [27] and the well-known Altman models [8]) they used quantitative (hard) financial data. Besides these hard data, qualitative (soft) data are used [9]. The early studies for Financial Credit Risk Assessment were univariate (a specific statistical method applied) studies which had important implications for future model development.

These laid the groundwork for multivariate studies. Ravi Kumar and Ravi [10] identify statistical and intelligent techniques to solve the bankruptcy prediction problem. For each type of technique, they describe the way they work. Chen, Ribeiro and Chen [11] summarize the traditional statistical models and state-of-the-art intelligent methods. In terms of performances, an accuracy rate between 81 and 90% reflects a realistic average performance based on the results of the analyzed studies [7]. The top five bankruptcy models with accuracy level of more than 80 per cent are

[9]:1) Altman [8], 2) Edmister [12], 3) Deakin [13], 4) Springate [28] and 5) Fulmer [29].

III. RESEARCH METHOD

The goal of this research is to identify and classify features that have been applied to determine Financial Credit Risk Assessment. In addition to the goal of the research, also, the maturity of the research field is a factor in determining the appropriate research method and technique. Based on the number of publications and identified features, the maturity of the Financial Credit Risk Assessment research field can be classified as mature. Mature research fields should A) focus on further external validity and generalizability of the phenomena studied or B) focus on a different perspective on the constructs and relationships between identified constructs [14].

Current studies have focused on selecting the best features to predict bankruptcy, while other studies have focused on comparing the efficiency and effectiveness of the different features identified. However, the analysis is always from a high-level and high latency perspective. Summarized, to accomplish our research goal, a research approach is needed in which the current features are explored, compared and mapped to the Financial Credit Risk Assessment Model. To accomplish this goal, a research approach is needed that can 1) identify features for Financial Credit Risk Assessment, 2) identify similarities and dissimilarities between features for Financial Credit Risk Assessment, and 3) map the features to the Financial Credit Risk Assessment Model. The first two goals are realized by applying a structured literature research and grounded theory. The purpose of the structured literature research is to collect the features. In addition, the purpose of grounded theory is to “explain with the fewest possible concepts, and with the greatest possible scope, as much variation as possible in the behavior and problem under study.” Grounded theory identifies differences and similarities by applying eighteen coding families. However, in our specific situation, an a priori coding scheme has been applied.

IV. DATA COLLECTION AND ANALYSIS

As stated in the previous section, the goal of this a research is to 1) identify features for Financial Credit Risk Assessment, 2) identify similarities and dissimilarities between features for Financial Credit Risk Assessment, and 3) map the features to the Financial Credit Risk Assessment Model.

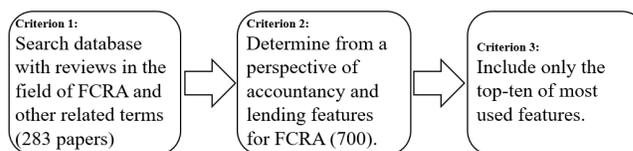


Figure 2. Feature Selection

The selection of the papers has been conducted via the link-tracing methodology [15], more specifically via snowball sampling. The snowballing was applied to take advantage of the social networks of identified respondents to provide a researcher with an ever-expanding set of potential contacts [16]. Snowballing is an effective and efficient form of contact tracing for use in diversity of research methods and designs, and apparently well suited for a number of research purposes [17] - [20]. In total, over 500 articles have been selected after which each paper was inspected for the inclusion of features. After this inspection, a total of 238 papers were included in the coding. For a study to be selected for coding, the study must explicitly address features for Financial Credit Risk Assessment (see Table I for details). This resulted in the identification of 700 features. Each of the 700 features have been added to a comparison table. After comparison, the features are coded. The unit of analysis for coding is a single feature, implying that one study can contribute multiple units of analysis.

Data analysis was conducted in one cycle of coding; the reason for one cycle of coding instead of three is the use of a priori coding scheme. The reason an a priori coding scheme was applied is because the concepts that needed to be coded were known upfront. To code the selected items the following question are asked: 1) is the feature a hard or soft feature? and 2) is the feature a relational or transactional feature? This process required inductive deductive reasoning. The inductive reasoning was applied to reason from concrete features to abstract elements. For example, the feature “net income/total assets” is a hard feature from a transactional perspective. Another feature is “the quality of management”, which is a soft feature from a relational perspective. The coding was done by one researcher while the other researcher acted as reliability coder.

V. RESULTS

In this section, the results of the data collection are presented. As described in the previous section, first features from existing studies have been analyzed. Therefore, the descriptive statistics with regards to the results of our coding processes are presented. After that, the description of the features from a DMN perspective are presented. The extraction of the features resulted in the registration of 700 features from 283 papers. From this sample, the top ten features were identified and selected; see Table I. Analyzing the defined features showed three results: 1) from an existing ranking perspective, 2) from a DMN perspective, and 3) from an information availability perspective.

A. Results from an existing ranking perspective

As stated in the literature review section, research indicates that the Altman model for bankruptcy prediction [8] is the most applied one. From our analysis, it shows that 4 out of 10 features (indicated by an asterisk) are applied by

Altman and that the fifth feature by Altman (Market Value of Equity/Total Liabilities) ranks thirteenth.

TABLE I. TOP TEN FEATURES

Feature 01: Net income/total assets	85 (papers)
Feature 02: current ratio	74
Feature 03: EBIT/total assets (*)	65
Feature 04: retained earnings/total assets (*)	62
Feature 05: working capital/total assets (*)	60
Feature 06: sales/total assets (*)	46
Feature 07: quick ratio	41
Feature 08: current assets/total assets	39
Feature 09: total debt/total assets	39
Feature 10: cash/total assets	32

B. Results from a DMN perspective

Analyzing the top ten features from a DMN perspective show four results. The first result: decision versus data input show that each feature is treated like a decision. The feature is derived from one or more conditions. For example, the first feature is derived out of two conditions: net income and total assets to which a mathematical formula is applied, in this specific case, net income divided by total assets. Each feature in the 10 retrieves the applied conditions from one data source, namely, the financial statements (the balance sheet and/or the profit and loss account).

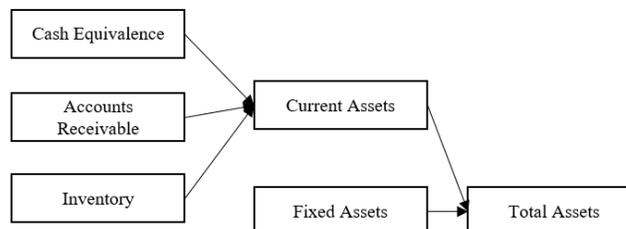


Figure 3. DRD-level elements

From the perspective of the financial statements, the conditions applied, e.g. net income, actually are data input since all are listed there. However, when analyzing one step deeper, each data input on the balance sheet or the profit and loss account is actually a decision. For example, total assets, is calculated as current assets plus fixed assets; see Figure 3. When analyzing all of the quantitative features selected, all features are derived from the balance sheet and/or the profit and loss account. A potential explanation of this phenomenon can be that the financial industry only looks at formal documents and formal statements. However, this raises the question if these combined features contain specific sub-decisions or specific input data elements that make them suitable for analysis. According to the researchers, this would be a subject to further investigate.

In addition, the features only apply information from the current financial statements. Formally, the balance sheet and

the profit and loss account have to be created once a year. Most companies create this information more times a year, voluntarily or obligatory. Also, not comparing information from early years, thereby indicating that the patterns have no additional information value. By analyzing the deeper layers underneath the features described previously, the hypothesis is that a better and quicker Financial Credit Risk Assessment can be performed.

C. Results from an information type perspective

As stated in this section, most features are based on data from the financial statements. Financial statements are, in most organizations, created once or twice a year. Therefore, the data needed to calculate the features is available once or twice a year. This causes an information opacity problem thereby reducing the effectiveness of the features. Other organizations that also assess the financial credit risk of an organization are banks, credit assessors, etc. Both previously also had to trust numbers that are published once a year. Since this time period is too long for both parties they searched for solutions to address this problem.

The bank addresses this problem by applying lending technologies. A lending technology is “a set of screening and underwriting policies and procedures, a loan contract structure, and monitoring strategies and mechanisms” [21]. Examples of lending technologies they apply are: leasing, commercial real estate lending, residential real estate lending, motor vehicle lending, and equipment lending, asset-based lending, financial statement lending, small business credit scoring, relationship lending and judgment lending. The same conclusion is realized by Ju and Sohn [22] who proposed to update the credit scoring model based on new features like management, technology, marketability, and business and profitability. Kosmidis and Stavropoulos [23] even got one step further in their conclusion, as they state that factors such as economic cycle phase, cash flow information and the detection of fraudulent financial reporting can evidently enhance the predictive power of existing models. Altman, Sabato and Wilson [24] reach the same conclusion as they state: “that qualitative data relating to such variables as legal action by creditors to recover unpaid debts, company filing histories, comprehensive audit report/opinion data and firm specific characters make a significant contribution to increasing the default prediction power of risk models built specifically for SMEs.” This leads us to the first conclusion that the financial industry should not only rely on hard features, which have a time delay, but also on soft information to assess the financial credit risk; see bottom left side in Figure 4.

To realize proper research in this area, the researchers have to go beyond the already cumulative features and look at the base data. E.g. no longer apply the cumulative feature: current assets but instead build features on the base information such as debtors information.

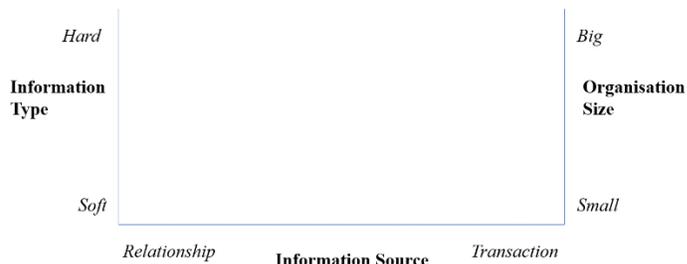


Figure 4. Financial Credit Risk Assessment Model

D. Results from an information source perspective

In addition to the type of information available, the data source and its fluidity are also factors. In financial literature, this phenomenon is called “the hardening of information” [21]. The concept “the hardening of information” states that because personal contact with the bank has decreased the banks rely more and more on hard quantitative information. However, if the model on which they base these conclusions is further dissected, two axes can be distinguished: A) the type of data and B) the manner in which the data is retrieved. The first axe describes the type of data that organizations retrieve to make a judgement about the financial credit risk. In the papers of Berger [21][25], the same distinction is made in an information type perspective: soft versus hard data. The second axe described the manner in which this information is retrieved. For example, two manners in which information can be collected are: 1) through face to face contact between a loan officers and the organization’s owner and 2) through a form on a website or any other digital manner. Since more banks, credit organizations, and accountants rely on the second, the statement of “the hardening of information” is that only quantitative data is used. Thereby underlying the fact that the traditional features are the most useful features to analyze going concern assessment. The main reason they state to support their claim is the adoption rate of technology.

However, a counter claim can be made that through the adoption of technology soft information can be more easily collected. For example, through firehose access to social media websites. However, this will depend on the type of soft or hard information one wants to retrieve because not all soft information can be retrieved through social websites, some still might need to be retrieved face to face. Therefore, the bottom part of our model, see Figure 5, indicates the manner in which the information is retrieved.

E. Results from an organization perspective

In FCRA literature, from a banking perspective, a distinction is made between the manner in which small and big banks assess the risk. Small banks apply more of a relationship perspective to assess the risk while big banks apply the analysis of transactions to determine the risk. Although this specific distinction cannot be found in

accountancy and lending (firms) literature, the hypothesis is that the same basic rules apply. Therefore, the right axe of the Financial Credit Risk Assessment Model contains the size of the firms assessing the risk; see Figure 4.

F. Overall Results

The overall analysis shows the following results. Most features are positioned in quadrant B, see Figure 5. The second most features are positioned in quadrant C. The other results show that none of the features are positioned in quadrant A and D, indicating a significant gap.

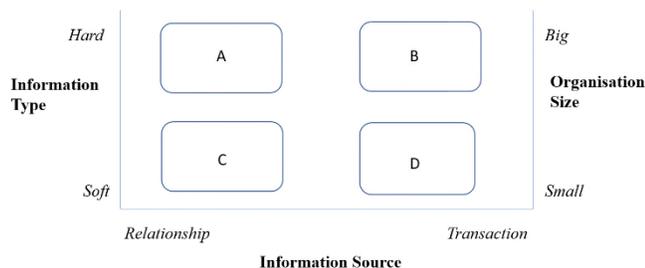


Figure 5. Overall Results with respect Financial Credit Risk Assessment Model

VI. CONCLUSION AND FUTURE WORK

In this paper, we aimed at finding an answer to the following research question: “*how to categorize financial credit risk features such that an integrative relationship is established with the information type applied and information sources used?*” To accomplish this goal, we conducted a literature study to identify features that have been designed and applied in previous research followed by coding the features based on an a priori coding scheme. The literature resulted in a total of 238 selected papers. From the selected papers, a total of 700 features were selected. Based on the a priori coding scheme, the features were mapped according to the following dimensions: A) the type of features applied, B) the information source applied and, C) the type of organization that applies the features. The results show that most features focus on hard information from a transactional source from official information with a high latency. In addition, the results show that most features still relate to the traditional Altman-Z score.

All the results have been mapped on the Financial Credit Risk Assessment Model, which is based on Wand and Weber [26], see Figure 4. The insights derived from this study provides a better understanding of the level on which the features are applied and where they score in the Financial Credit Risk Assessment Model. This will enable further exploration and identification of features that have a low latency but still have a proper predictive power. From a practical perspective, our study provides an overview of

features that can currently be applied, and which further exploration should be taken into account.

While we provide an integrative overview of features for Financial Credit Risk Assessment, our study is not without limitations. The first limitation concerns the sampling and sample size. The sample group of features is drawn from the identified paper without taking into account the effectiveness of the features selected. The main reason for this choice is the fact that not all papers report on the effectiveness of the features applied. While we believe that for the purpose of this study this causes no problems, further refinement of the features selected is recommended. Additionally, our results should be further validated in practice.

We believe that this work represents a further step in research on classifying and creating new features for Financial Credit Risk Assessment. While this work has focused on classifying current features, future research should explore subcategories, reducing the high latency for hard information and to research more features from a relational/soft perspective and relational/transaction perspective.

Further research should focus on reducing the high latency for hard information and to research more features from a relational/soft perspective and relational/transaction perspective.

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