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SYNTHETIC READING OF THE DIFFERENT APPROACHES AND MODELS FOR ASSESSING THE RISK OF BUSINESS FAILURE.

LECTURE SYNTHÉTIQUE DES DIVERSES APPROCHES ET MODÈLES D'ÉVALUATION DU RISQUE DE LA DÉFAILLANCE DES ENTREPRISES

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Abstract

The interest of this present research work is to try to study the academic corpus related to the subject of the failure of companies in order to be able to better apprehend it.
The examination of the literature which resulted from it allowed us to raise and to study on the onehand, the existence of three types of approaches, namely the static, dynamic and processual approach of the failure of the companies and on the other hand the existence of several types of statistical and probabilistic models allowing to evaluate and to prevent at best the risk of the failure.
Keywords: Failure, process, approaches, models.
JEL Classification : C14, G33, K35, P17

Résumé

L'intérêt de ce présent travail de recherche est d'essayer d'étudier le corpus académique lié au sujet de la défaillance des entreprises afin de pouvoir le mieux l'appréhender.
L'examen de la littérature qui en découlait nous a permis de soulever et d'étudier d'une part, l'existence de trois types d'approches à savoir l'approche statique, dynamique et processuelle de la défaillance des entreprises et d'autre part l'existence de plusieurs types de modèles statistiques et probabilistes permettant d'évaluer et de prévenir au mieux le risque de la défaillance.
Mots-clés : Défaillance, processus, approches, modèles.

Introduction

The outbreak of the Covid-19 crisis, the outbreak of Russia's war against Ukraine, the general risein global prices, etc., were unprecedented sources of upheaval for the Moroccan and global economy. Several efficient companies were condemned to bankruptcy, others were still strugglingto maintain their activity and many small ecosystems were simply doomed to disappear (Guerini & al., 2020). The most common challenges faced by businesses, and SMEs in particular, were amplified and business failures soared, scandalously, noting, at the end of 2021, a 331% increase compared to 2009, a 25% increase compared to 2019 and a 59% increase compared to 2020 with arecord number of bankruptcies of 10,556 cases (Kadiri, 2022). As such, and in view of this context,we have deemed it useful to conduct this research work in order to be able to approach, more closely, the notion of business failure and to deal with its various approaches and predictive modelsallowing to better understand it.
In fact, business failure has been, for several decades, the subject of a good number of works in thefields of economic and social sciences and the majority of them considered it as the situation for which the company remains unable to continue its activities both in national and international markets and consequently remains forced to lay off its employees. It can be sudden, unpredictable and difficult to mitigate, as well as being largely progressive, prolonged and the result of a process of "natural selection" leading to the disappearance of the company (Amankwah-Amoah & al., 2021). The first works established in this sense go back to the 1930s with the contributions of Fitzpatrick (1932) and Merwin (1942), who were particularly interested in evaluating the risk of failure to which firms are exposed, in proposing predictive models of this risk (Balcaen & Ooghe, 2006), in determining its causes and/or in understanding the processes leading to the disappearanceof the firm (Balcaen & Ooghe, 2006); Claveau et al., 2018). In another sense, the main objective ofthe majority of the works, carried out in this field, is most often to improve the

prediction, the prevention and/or the understanding of this phenomenon in order to be able to skilfully circumvent it (Claveau, et al., 2018).

Therefore, the research question that emerges from this context is: In a dynamic and multidisciplinary understanding of the notion of failure, what are the various approaches and main predictive models, evoked by the literature and allowing to evaluate, at best, the risk of business failure? In order to answer this question within a well-defined research framework, the study of the literature analyzing the difficulties of companies, these last decades, challenged us to adopt a logic purely, descriptive of the various approaches of evaluation of the risk of the failure of existing companies with a synthetic presentation of the principal statistical and probabilistic models of evaluation of this risk. The objective is to help any researcher interested in the study of the failureof companies to adopt the approach and the adequate model, allowing him to apprehend in an effective and dynamic way the various aspects related to this subject.

To do so, we will first present an overview of the various approaches to assessing the risk of failure, then we will present the main traditional statistical models for assessing this risk, followed by a presentation of the main alternative predictive models such as the "Logit" model, neural networks, expert systems, etc.

1. Business failure

Business failure is, a vague, polysemous and multidisciplinary concept. To describe it, authors use different terminologies: the death of the company, cessation, bankruptcy, dissolution, insolvency, filing for bankruptcy or closure. It is observed at the moment when the company is no longer ableto satisfy its economic, financial and social objectives in a continuous manner (Brédart & Levratto,2018; Sangué-Fotso & Molou, 2021a).

1.1. A concept with a multidisciplinary aspect

According to Kherrazi and Ahsina (2016) "Business failure has undergone a multitude of definitions since authors and researchers became interested in this phenomenon, which became a field of investigation in its own right after the crisis of the 1930s (Fitzpatrick, 1932)" (Kherrazi &Ahsina, 2016: 54). This multiplicity of definitions generally finds its explanation in the intense variety of theoretical and empirical contributions that have contributed to the analysis of this phenomenon by referring to several economic, financial, managerial, and legal acceptions (Cata &Zerbib 1979; Brédart & Levratto 2018; Sangué-Fotso & Molou, 2021).

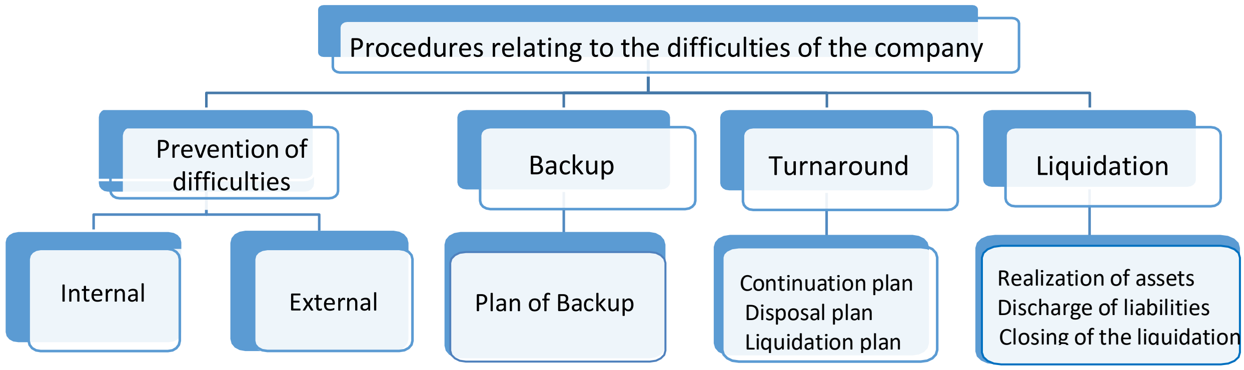
In the economic sense, business failure corresponds to the deterioration of the overall state of thefirm in terms of value added, performance (Ooghe & Van Wymeersch, 1986; Crucifix & Derni 1992; Zopounidis, 1995) and economic situation (Bescos, 1987). Thus, Liou and Smith (2007) consider a firm in difficulty to be a firm in which maladjustment to the economic environment is manifested as a result of poor economic conditions (Kellens 1974; Johnson 1974), inflation (Altman, 1984), debt conditions (Khoufi & Feki, 2004), sectoral policies, public support measures, decline in performance, etc.

In the financial sense, the concept of default is, frequently, considered to be a state of financial distress (Kherrazi & Ahsina, 2016), translated by the deterioration of the accounting and financial ratios which, over time, leads the firm to bankruptcy (Boubakary, 2020). These ratios are based, mainly, on the study of the financial structure (Modigliani & Miller 1958, Belletante, et al.,2001), profitability, solvency and net cash flow.

In a managerial and strategic sense, the assessment of the risk of failure of any company is considered, potentially, dependent on the internal (human, technical, financial, organizational) environment (Guilhot, 2000; Ooghe & Waeyaert, 2004; Pompe & Bilderbeek, 2005; Thornhill &Amit, 2003, Aleksić, et al., 2013) and external to the firm (competition, market, legislation, etc.)(Lawrence & Lorsch, 1989, M'Rabet & Tazi, 1991, Mintzberg & al. 1999; Guilhot, 2000; Ooghe & Waeyaert, 2004, Boubakary, 2020).

In the legal sense and according to Moroccan legislation, a company is in default from the moment it declares a cessation of payments manifested by the opening of a collective procedure related tobusiness difficulties (Law No 73-17). The cessation of payments means that a debtor does not manageto pay the due date of the debt that has become due. A single payment incident is largely sufficient,from a legal point of view, to give rise to the event of default and to bring the company into the judicial liquidation procedure (Ben Jabeur, 2011). This seems to be the last option for a failing company when it is no longer viable. It simply sells its assets (tangible and intangible assets) in order to be able to repay a maximum of (Zammel & Normandeau, 2020). It is nevertheless important to note that, generally speaking, liquidation remains the outcome of the majority of procedures in nearly 80% of cases (Claveau et al., 2018). In Morocco, this rate rises to 90% of cases.

Figure 1. Procedure relating to business difficulties in Morocco



Source: Authors according to Law No 17-73

Moreover, it is important to specify that this binary opposition between bankruptcy and survival cannot cover the various procedures established by Moroccan law. The exit routes and the forms of closure of the activity are multiple, while passing by the procedure of safeguard, we evoke the deposit of bankruptcy, the procedure of recovery or the legal liquidation.

Thus, by qualifying business failure on the basis of procedures relating to business difficulties, weexclude several cases of market exits that escape the judicial process. Voluntary cessations and amicable liquidations generally leave no footprints, making this phenomenon of business evaporation difficult to quantify.

In view of this observation, attributing a unanimous and univocal definition to this phenomenon and describing it in a clear and concise way remains, then, a delicate and complex mission.

It is in this sense, then, that several academics have recalled the need to understand business failure without restricting it to the sole procedural situation and to consider it as a continuous process of deterioration of capacities and performance that leads, or not, to legal proceedings (Zammel & Brédart, 2020).

1.2. Business failure: a sort of gradual process

Several authors attribute the processual aspect to the failure and considered it as the result of a process of "natural selection" that finds, generally, its origins in a combination of interrelated factors of economic, contextual, organizational, strategic, financial and operational nature, let us speak of a "path of failure" (Kœnig, 1985) or a "spiral of failure" (Argenti, 1976; Marco, 1989; Crutzen and Van Caillie 2007; Claveau et al., 2018), with default as the final stage of this process (Brédart & Levratto, 2018).

Overall, the description of this process varies according to whether the failure is voluntary or involuntary. In the case of **voluntary** (or strategic) **failure**: It corresponds to the firm's desire to

use the rules governing the procedure for dealing with business difficulties to its advantage in order to renegotiate its contracts (Delane, 1992). Such a strategy remains attractive, as long as the legislative system remains fragile, failing and making it easy to break contracts with the various stakeholders while escaping liquidation (transaction cost theory). Therefore, an efficient and flexible legislative system must impose rigorous constraints and adequate legal mechanisms to ensure the safeguarding of profitable firms in financial distress (Malécot, 1991; Blazy, 1996).

In Morocco, the local legal system on the restructuring procedures of distressed companies seems, relatively, deficient, inadequate and in total absence of statistics or official data, despite the "existence of a legal basis for proactive publication, based on Article 10 of Law No 31-13 and relatingto the right of access to information" (Laraqui, 2022). In this respect, the collective procedures provided for in the legislation in force (safeguard/recovery) remain, more or less, sterile, and do not produce, enough, the expected results on the ground (Ibriz, 2022).

As for **involuntary failure,** it corresponds to a succession of stages leading to a decline in performance up to the point of insolvency (Blaz and Combier 1993). The decline in performance may correspond either to a temporary cash flow crisis (illiquidity) or to a lasting deterioration of the business (insolvency) (Wruck 1990). When a company can no longer meet its financial commitments, given a level of profitability that is too low, it is in **default of payment** (financial distress[1]). Depending on the legislation, a simple cash flow crisis is sufficient to trigger the procedure for dealing with business difficulties; conversely, other systems provide for its triggeringwhen the payment default is chronic. When the company is in a state of **cessation of payments** (filing for bankruptcy), the problem arises as to how to deal with the financial difficulties out of court (Refinancing, modification of the debt contract, informal renegotiation, etc.). If the procedureis not successful, the formal rules defined by the legislator will apply, by default, and it is this event which then constitutes **a default in** the strict sense of the term (bankruptcy).

Thus, with regard to this distinction between voluntary and involuntary failure, it is important to point out that cases of voluntary failure are generally few in number and concern, relatively speaking, larger firms. For small and medium-sized firms, failure is more involuntary (Blazy, 1996).

In fact, several authors have been much more interested in the involuntary perspective, such as

[1] "A firm is considered to be in financial distress if it is unable to meet a credit deadline after 90 days from the due date (Circular n° 19/G/2002 of Bank Al-Maghrib 2002)." (Zizi, et al., 2021 :4)

Argenti (1976), Laitinen (1991), Blazy (1996), Thornhill and Amit (2003), etc., and have shown that the process of business failure can differ from one firm to another, depending on its intrinsic characteristics (age, size, sector of activity, management style, etc.) and extrinsic causes linked toits interaction with the context.

Marco (1989), for example, emphasized management and prevention errors as the first cause and first step in a long and progressive process of performance degradation.

Crutzen and Van Caillie (2009), on the other hand, built on the work of Marco (1989) and represented, in a different way, the process of business failure in four main phases:

1- The observation of the **origin of the difficulties** which are, generally, attached to problems related to the general, economic, competitive and managerial environment of the company as well as to problems related to the insufficiency of the resources of the company and the multiplication of its errors of management.
2- The appearance and deterioration of **the symptoms of failure,** materialized by losses of marketshare, competitiveness and profitability, notable insufficiencies in terms of self-financing, liquidity, and indebtedness with an increase in financial charges.
3- The appearance of **warning lights** and signals, following the fall of solvency, liquidity and theexacerbation of the mistrust of lenders, let the company enter a downward spiral of financial failure.
4- The observation of the **bankruptcy of** the company, following the degradation of the strategic position of the company, the shortage of its resources, the lack of liquidity and solvency and theinefficiency of the management policies (operational, commercial and financial) registering it in the state of cessation of payment.

In the light of this reading, it seems useful to point out that business failure is rarely considered a sudden and unpredictable event. It is generally part of a gradual process of deterioration in performance, the risk of which is generally accentuated in times of crisis.

As such, and in order to properly understand this notion of failure and assimilate its different aspects, it is advisable to understand it under three main approaches put forward by the literature, namely the static, dynamic and/or processual approach, and to analyze it via one of the statistical and/or probabilistic models of risk assessment of its appearance, conceived by various authors andresearchers who have made failure their battlefield.

2. Approaches to assessing the risk of failure

As already noted, the disappearance of a firm is, exceptionally, a sudden event. It is the result of a combination of interdependent and evolving causes over time of a financial, managerial, strategicand operational nature, highlighting the processual aspect of the failure. Moreover, it is importantto specify that failure is also considered as a phenomenon whose observation is based on the legalperspective of the concept (Altman, 1968; Bardos, 2001). Its study is generally associated with a range of exogenous and/or endogenous factors, whose prediction is more or less delicate and generally refers to the risk of "cessation of payments" or even liquidation. Business failure also refers, more often than not, to the financial distress manifested by one or more cases of default (sometimes observable years in advance), leading the company to disappear (Claveau, et al., 2018). Although several authors have adopted this approach and considered default as the first sign of business failure (Beaver, 1966; Deakin, 1972; Ward & Foster, 1997; Brédart & Levratto, 2018a), however, it should be noted that their attempts were almost never successful, to the point that thisnotion is no longer used to understand the concept of failure (Bredart & Levratto, 2018). As a result, and in order to qualify the strict assimilation of default to failure, several authors have considered the latter to be the state from which the firm "is no longer able to achieve its objectives(economic, financial, social) in a regular manner. In this respect, and for reasons of scientific clarity, it seems necessary to us to synthesize the various works related to this subject into three main approaches: (1) the predictive approach based on the identification of the various symptomsof failure; (2) the explanatory approach based on the determination of the various causes of failure;and (3) the comprehensive approach based on the dynamic processual aspect of failure.

2.1.The static-predictive approach

The most important and oldest research goes back, mainly, to the works of Beaver (1966) and Altman (1968), and belong, mainly, to the first category of works based on the financial analysis of balance sheets via the study of profitability, debt and liquidity ratios as unavoidable factors in predicting failure. They distinguished companies into two categories (healthy/bankrupt) and aimed,through more or less sophisticated models, to better predict the probability of company failure, by using a certain number of statistical tools (discriminant analysis and logistic regression) and by identifying certain combinations of ratios and accounting and financial indicators. More generally,these studies make it possible to detect the symptoms of failure, to identify the early signs of possible difficulties and, in turn, to predict the disappearance of firms (Ohlson, 1980; Zavgren, 1983; Platt & Platt, 1990; Claveau, et al., 2018). However, more

recently, at the end of the 2000s,these classical statistical failure prediction techniques continue to have a number of limitations (Balcaen & Ooghe, 2006) and prediction studies based on artificial intelligence such as neural networks or genetic algorithms seem to be emerging and conquering academic fields by presentingsophisticated tools capable of handling complexity and multidisciplinarity (Yang, Platt & Platt, 1999; Claveau, et al., 2018). Nevertheless, it is important to emphasize that whatever the techniqueapplied, the results obtained generally provide a score that acts as a warning signal in the event ofa risk of default (Bardos, 2001; Claveau & al., 2018) This allows banks and other capital lenders to anticipate any default at an early stage. However, although they appear to be effective, these tools also appear to be insufficient, presenting several constraints that limit the credibility of the predictions made (to a level that only reaches 90% of cases), and thus leading banks to make decisions that are not economically rational (Séverin, 2020).

In this respect, and with regard to these various constraints, it remains that this approach based mainly on symptoms does not provide sufficiently global and in-depth explanations of the phenomenon of failure, insofar as statistical calculations and analyses of financial ratios only lead to a classification of companies (failing/non-failing), giving a static short-term view, without taking into account the underlying causes allowing a more global understanding of this phenomenon.

2.2.The dynamic-explanatory approach

Given the important number of limits addressed to the predictive approach, a good number of authors have focused on the search for the causes of failure, studying it in depth, and concluding that only a global qualitative approach of the economic, strategic, managerial and organizational aspects (Crutzen & Van Caillie, 2007) will allow the detection of the different explanatory causes of the failure. Marco et al. emphasized, for example, management errors and the lack of experience of the manager. Julien (1998), on the other hand, emphasized the lack of managerial skills, particularly in finance, and the inadequacy of financial resources, particularly undercapitalization.Carter and Van Auken (2006), for their part, agreed with these causes and added the economic context as a primary determinant in explaining business failure. Altman, in his 1984 work, and several other subsequent authors, also confirmed this inclination, attached to qualitative and macroeconomic variables and considered that the turnover and profitability of firms are closely linked to the economic situation of the country, the main indicator of which is

the GDP. It is in this sense that any economic downturn intensifies competition, accelerates the restructuring of companies and even forces them to take more and more commercial risks. The growth rate of the consumer price index (CPI) is also considered to be an indicator that is strongly correlated with the willingness of companies to survive, especially in the short term, insofar as the rise in prices supports marginal companies by reducing their competitiveness and their debt, as well as protecting their inefficiency at a time when consumers are tending more and more to buy lower quality products. (Coulibaly, 2004). However, in the medium term, firms are slower to respond to accelerating inflation, as costs tend to rise faster than selling prices. As a result, and in the face ofrelatively uncertain expectations about the evolution of the inflation rate, the vulnerability of firmsis exacerbated and the risk of default becomes increasingly imminent.

2.3.The processual - comprehensive approach

Works based on the sequential aspect have also evoked the complexity of default, considering it asa continuous process having, its origins in an evolving combination of endogenous and/or exogenous factors with a multidisciplinary character leading to the cessation of payment. It is triggered by small problems that gradually develop into more serious ones (Daubie & Meskens, 2002); (Bredart & Levratto, 2018) This makes the prediction of default a delicately attainable objective. It is in this sense, then, that a number of authors have proposed dynamic models based on failure profiles referring to multiple contexts in which mismanagement, the manager's bad behavior and his or her inability to manage external disturbing factors articulated in a chronologicalsense, play a primary role in the deterioration of performance and consequently in the explanationand understanding of business failure.

Unfortunately and until now, this work has not received enough attention and "no unanimously recognized unifying theory has yet been presented in the literature (Dimitras et al., 1996), while the various authors who have studied this aspect of the phenomenon of business failure have approached it from different points of view that have not yet been reconciled"(Crutzen & Van Caillie, 2007: 3) (see paragraph 2.2.).

Figure 2 : The three approaches to assessing the risk of failure

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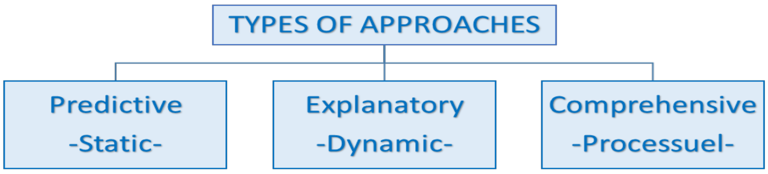

Source : Authors

More generally, the inventory of the various works cited above allowed us to consider that all the approaches to business failure developed, so far, sought to determine the most suitable path to explain, understand and predict the state of businesses. To do this, several techniques, tools and models for assessing the risk of failure (Brédart, 2015) are then designed and classified in two main categories: the traditional models of failure risk assessment based on Beaver's unidimensional model and Altman's discriminant analysis as well as the alternative predictive models based on regression on qualitative variables (Nokairi, 2018), neural networks, expert systems and external rating systems.

3. Overview of traditional statistical models for assessing default risk

The hypothesis of Guilhot (2000) which stipulates "It is more important to foresee bankruptcies than to search for their causes" (Ben Jabeur, 2011) ardently reminds us of the necessity to foresee the failure of companies and to anticipate the possible risks likely to slow down the normal trend of their life. In fact, the multiplication of economic and financial difficulties that companies are increasingly confronted with, and the increase in the number of disruptive forces in the context, have led to a strong upward trend in the number of declared bankruptcies, suggesting an increased need to resort to predictive models of the risk of failure.

Indeed, during the last six decades, several studies on the prediction of the risk of failure of firms have been developed. Beaver (1966) was the first to propose a unidimensional dichotomous classification based on a single ratio. Later, Altman (1968) incorporated several ratios at once intothe model using multiple discriminant analysis. The author also developed a Z-score model, allowing the company to be classified in the group to which it is closest (bankrupt or healthy), thusachieving a successful front. However, in view of the various limitations observed, several other alternative predictive models were developed and aimed, mainly, at giving more predictive precision to the risks incurred.

3.1. One-dimensional Beaver model

Since the 1960s, a number of authors have attempted to assess the risk of failure of firms based onthe financial analysis of accounting data. Of course, the techniques adopted are multiple, but the general principle underlying most of the studies is the same: exploit the ex-post knowledge of the future of firms (Ben Jabeur, 2011) by relying on statistical comparison techniques such as Beaver'sunidimensional model (1966).

Also called "Univariate Discriminant Analysis", the principle of Beaver's unidimensional model is based on the consideration of a single accounting measure, i.e. a single financial ratio, while ignoring the others. The objective is to determine the ability of the latter to classify firms in the same initial sample (bankrupt and healthy) and to predict the possible risk of failure of a firm in another sample.

Otherwise, it is a question of comparing the financial ratios of failing firms with those of healthy firms (Nokairi, 2018), and then identifying any differences that may exist between the two groups in order to be able to predict the risk of failure as well as possible.

According to this model, the ratios that yielded the lowest company misclassification rate were generally: Net Income/Total Assets; Cash Flow/Total Debt; Working Capital/Total Assets; Total Debt/Total Assets and Current Liabilities/Total Debt.

Admittedly, this model has the advantage of being simple and efficient and allows us to obtain relatively satisfactory results. However, it seems to be very fragile and inconsistent in that it neglects the strong interdependence of the ratios and their joint effect. In fact, when each ratio is analyzed separately, it risks leading to antinomic results, making the assessment of the risk of default very formidable.

3.2. Multiple discriminant models

Based on the analysis of historical data, on linear discriminant analysis and on statistical exploration, the first discriminant models were developed in the 1960s in the United States, particularly by E. Altman (1968), before they were developed and extended in Europe and then particularly in France.

Also called multivariate discriminant analysis, these models bring together all the methods that make it possible to combine and transform several ratios into a single indicator that can discriminate, on the basis of individual characteristics, between healthy and failing firms. (Djongoué, 2015), on the basis of individual characteristics, healthy firms from failing firms

(Elhamma, 2009), by establishing a causal link between the economic and financial characteristics of borrowers and their probability of default (Brédart, 2015).

In order to be able to classify, efficiently, a company in one of the two groups (failing or healthy), Altman has developed, two main prediction models of failure:

The first model: Altman's model (1968) is based on the use of several ratios (discriminating variables) processed simultaneously via Multiple Discriminant Analysis (MDA). The model was based on a sample of 66 firms, including 33 healthy firms and 33 failing firms. From a set of 22 ratios, taken from accounting and financial documents, Altman distinguished five main ratios considered to have the greatest discriminating power and the strongest predictive value, providing information on the liquidity, profitability, solvency, growth and activity of the company.

As such, the discriminant function consists of these five ratios (Working capital / Total Assets, Reserves / Total Assets, Earnings before interest and taxes / Total Assets, Market value of equity /book value of total liabilities and Sales / Total Assets) (Trabelsi-El Gharbi, 2009; Zizi, et al., 2021) and is formulatedas follows: $Z = 0.012\ X1 + 0.014\ X2 + 0.033\ X3 + 0.006\ X4 + 0.999\ X5$ (Nokairi, 2018).

The results revealed that any company that scored 2.99 or higher was healthy (in the safe zone). Companies that scored below 1.81 were considered to be failing (in the distress zone). Those witha score between 1.81 and 2.99 are said to be ambiguous signal companies (in the uncertainty zone).Through this model, the results also showed rates of 95% of firms ranking well one year before failure, 72% two years before, 48% three years before, 29% four years before, and 36% five yearsbefore (Nokairi, 2018). As such, the model has proven to be very successful and has been widely used, worldwide, given its simplicity, effectiveness and robustness.

However, given that the model is based on the ADM which requires restrictive statistical conditions (normal distribution of the explanatory variables, similarity of the variance-covariance matrices forthe two groups of the sample, etc.), given the narrowness of the sample size studied and given theparticular focus on listed manufacturing firms, Altman's model has raised doubts about its accuracyand the relevance of its coefficients, thus leading E. Altman to develop another new z-score model to counteract these limitations.

The second model: the z-score or "Zeta Model" is a new business model developed by Altman, Haldman and Narayan in 1977 and incorporating the advances in discriminant analysis at that time. It is based on the study of 28 new classification variables leading to a discriminant function consisting of seven ratios (variables) providing information on liquidity, profitability, solvency

andrisk. The sample is considered to be more representative of the firms and the problems of failure (restated accounting data, size of firms, recent failures, etc.) and is composed of 53 bankrupt firmsand 53 healthy firms for the period from 1969 to 1975.

The values taken by the score (the variable) Z are supposed to be as different as possible from onesubset to another (Elhamma, 2009). This score Z is expressed, generally, by the following discriminant function: $Z = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_n X_n + b$ With :

X_i: Accounting and financial ratios; α_i: Coefficients attached to the ratios; b: a constant.

It should be noted that no score function has absolute discriminating power; there is often a zone of uncertainty between the two categories of firms, which generates two types of errors: Errors of the first type: for which the score classifies failing firms among healthy firms; and Errors of the second type: for which the score classifies healthy firms among failing firms (Elhamma, 2009). Apart from the vagaries of the error zone, the Zeta model, also known as the scoring method, wasable to produce good company ranking rates up to a five-year horizon. In fact, compared to the 1968 Altman model, the Zeta model gave similar results for the one-year horizon (95%), approximately better results for the two-year horizon (89%), and much more accurate results for the classification of failures for the three-, four-, and five-year horizons prior to failure, with, 83.5%,79.8%, and 76.8% of good classification rates, respectively.

More globally, discriminant models have contributed greatly to the improvement of the predictionof the risk of business failure by allowing a simpler and more efficient automation of the credit granting procedure, a faster analysis of the different financial aspects of the business, a significantreduction in the cost of banking services and a better control of the response time of credit requests (Barmaki, 2005).

It should be added that in addition to the Altman and z-score model, other discriminant models have been developed, based much more on samples composed exclusively of SMEs and leading tothe development of other discriminant functions composed of a battery of ratios different from those proposed by Altman. These include the model of Collongues (1977), the model of Conon and Holder (1979), the model of Loeb and Portier (1984) and the discriminant model of Bardos (1989) established for the Banque de France following the use of data from its Central Balance Sheet Office. Other (discriminating) Scores functions of the Banque de France also emerged following the increase in cases of business failure in France during the 1980s and early 1990s, placing much greater emphasis on certain qualitative variables (2003), mainly around three themes linked to thebusiness cycle (Barmaki, 2005) such as the slowdown in economic activity,

management difficulties and financial difficulties. However, despite their interest and wide dissemination in financial and business circles, the fact remains that the models of multiple discriminant analysis 481 have been widely criticized by a number of authors (Alves 1978, Ohlson; 1980; Zmijewski, 1984, Jooset, 1998) given that the results obtained are based on strict statistical conditions (normality of the variables, equal dispersion of the groups of firms, etc.) and on restrictive hypotheses that may be unverified for the financial data.

As a result, and in order to overcome these statistical and transposition limitations, several researchers have attempted to integrate qualitative and/or strategic variables (macroeconomic data,quality of management, market, stakeholders, etc.) into the financial ratios in order to obtain betterrankings of firms and thus be able to properly assess failure (Barmaki, 2005).

As such, new alternative predictive models have emerged and have set the objective of developing new models that are better adapted and more reliable for failure prediction. We cite among others: the probability models "Logit and Probit", neural approaches, genetic algorithms, etc.

4. Overview of the main alternative predictive models

In addition to the traditional models for assessing the risk of failure mentioned above, several alternative research projects have been developed and have made it possible to develop new tools for predicting the failure of companies. In this section, we will only mention those that are considered to be the most widely used and most interesting, namely: conditional probability models, neural networks, expert systems and external ratings.

4.1. Logit and Probit probability models

Faced with the constraint of multinormality of variables in discriminant models, several authors have preferred to resort to other methods and parametric techniques, more appropriate and assuming a different distribution of accounting variables based on the use of econometric techniques on qualitative variables (Ben Jabeur, 2011), Such as the Logit model (obeying a logisticdistribution) and the Probit model[2](obeying a centered reduced normal distribution).

In fact, the principle of the Logit model, more frequently used in the academic literature, is that it does not require any assumptions to be made about the distribution of the variables, nor about thevalues prior to the failure (Ohlson, 1980; Zavgen, 1983).

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[2] The Probit model is similar to the Logit model. The main difference is in the way the probability P (X, : p) = F (a + βX,) is calculated, where F(a+ βX,) is a cumulative standard normal distribution function(Barmaki, 2005).

It is based on a cumulative logistic regression function giving, directly, the probability that a firm belongs to one of the two groups specified a priori, according to its financial characteristics.

It is for this reason that the Logit model, also known as logistic regression, is considered a probabilistic binomial regression model [0,1] of the generalized linear model family, used to deal with two-group classification problems, such as predicting the failure of a company. In the United States, Ohlson (1980) was the first to use this method to predict business failure. After that, logistic regression gained popularity and is considered one of the most widely used methods in the world for predicting business failure (Shi & Li 2019; Zizi, et al., 2021).

It is in this sense then that the basic techniques of the Logit model have been massively developed and extended by other researchers in order to obtain better results for the classification of firms (Bardos 1989, Collins and Green 1982, Hamer 1983).

Charalambakis and Garrett (2019), for example, employed a multi-period Logit model on a sampleof 31,000 Greek firms between 2003 and 2011. The model classified 88% of the firms that defaulted during the Greek debt crisis and proved that it retains its predictive ability over various time horizons (Zizi, et al., 2021).

Khlifa (2017), on its side, developed a logistic regression (Logit) model predictive of the risk of default on a sample of 2,032 Moroccan firms of which 1,664 are SMEs. The results of the model gave good classification rates of 88.2% over two years before default and this compared to other probabilistic models and intelligent models (Khlifa, 2017).

Zizi, Oudgou and El Moudden (2020), for their part, built a binary logistic regression model on a sample of 90 SMEs in the Fez-Meknes region and their results revealed an overall classification rate of 91.11% three years before the failure and 84.44% two years and one year before the failure (Zizi, et al., 2020).

More generally, the results of good ranking of the Logit model, are confirmed by several other authors (Iturriaga & Sanz, 2015; Du Jardin, 2015; Affes & Hentati-Kaffel, 2019), who have, scrupulously, demonstrated that logistic regression models are the best models that offer more accuracy in predicting failure than multiple discriminant analysis (Zizi, et al., 2021). However, it is important to specify that, in parallel and with the technological change, artificial intelligence hasallowed, on its side, to refine the prediction of the failure of companies thanks to genetic algorithmsand efficient neural networks (Idrissi & Moutahaddib, 2020) which were quickly developed through the use of machine learning techniques.

4.2.Neural networks

Recent studies in the field of artificial intelligence, have focused on more advanced and sophisticated methods to build more accurate prediction models (Schalck & Yankol-Schalck, 2021). One of them is the Artificial Neural Network (ANN) method. The principle is to develop analgorithm that reproduces the functioning of the human brain in the process of information processing (Chaney, 2008). The use of neural networks in the field of business failure prediction was first introduced by Odom and Sharda (1990) (Zizi, et al., 2021).

Afterwards, these models have been widely adopted by several other authors (Zizi et al., 2021) as they are characterized by nonlinear and nonparametric adaptive learning properties (Schalck & Yankol- Schalck, 2021) that do not require a prior specification of the form of the function to be used, nor the adoption of restrictive assumptions on the statistical distribution of the explanatory variables (Barmaki, 2005).

It is in this sense then that, during the last three decades, neural networks have shown promising results in terms of predicting the risk of failure, thus constituting one of the machine learning techniques with a very high prognostic capacity (Zizi, et al., 2021) and allow to obtain classification results superior to those of discriminative models or conditional probability models.

Ciampi and Gordini (2013), for example, applied ANNs to a sample of 7,000 Italian SMEs and found that ANNs make the best contribution to the assessment of SME credit risk with a predictive accuracy, particularly, high for small firms. Barboza et al. (2017), on the other hand, demonstrated that machine learning models have, on average, 10% higher accuracy than traditional models (Schalck & Yankol-Schalck, 2021).

Zhang et al (1999) found, on the basis of a matched sample of 220 U.S. firms, that ANNs clearly outperformed logistic regression models in terms of ranking rate. Chen and Du (2009) also used the ANN model on 68 firms listed on the Taiwan Stock Exchange (TSEC) by analyzing 37 financial ratios. Their results showed that neural networks are a very effective technique for predicting the financial distress of firms with an accuracy amounting to 82.14% two years prior to failure.

Paule-Vianez et al (2020), on the other hand, used the hidden layer artificial neural network model to predict firm failure in Spain. They found an accuracy higher than 97% on a sample of 148 Spanish financial institutions and proved that neural networks have a higher predictive capacity than multiple discriminant analysis.

More globally and according to the results of a large European study, Altman et al (2020) compared the performance of several default prediction methods and concluded that neural

networks and logistic regression were superior to other predictive models at the level of efficiency, performance and predictive precision (Zizi, et al., 2021).

Nevertheless, it is important to point out that the neural network method has a major disadvantage linked, mainly, to the lack of transparency in the use of explanatory variables within the network connections, called the black box syndrome (Zizi et al., 2021). However, with discriminant analysisor Logit and Probit models, this problem is almost non-existent insofar as it is generally easier to identify the discriminating power of each explanatory variable in these models.

More generally, artificial neural networks are a very promising field in which research into default risk assessment is very active. However, given the presence, at present, of a certain number of problems of opacity and efficiency related to the exact and precise evaluation of the risk of failure of companies, a certain number of alternative techniques of prediction and prevention of failure have appeared, such as the method of expert systems.

4.3. Expert systems

Expert systems are experience-based decision support tools based on subjective, declarative reasoning, inspired by accounting, financial, economic and sectoral data. They allow to simulate the logical reasoning of a human expert, described in a knowledge base of rules and facts, thanks to an interactive system based on a man-machine dialogue (Barmaki, 2005). These rules are established in a completely empirical way, by questioning the credit experts on their practice and their experience (Sadi, 2010). The weighting of these rules makes it possible to measure the credit risk of the company (the borrower) by assigning it a score. The construction of such a system requires an explicitation of the expertise, by transforming the implicit knowledge into a system ofexplicit rules. Otherwise, the confrontation of practices leads to norms and rules formalized by means of rating grids and weighting factors (Brédart, 2015).

Nowadays, expert systems are becoming more and more popular, especially in the field of credit risk assessment. Among the most frequently used expert systems, we cite the CREDEX (expert credit) system of Pinson (1992) and the CGX system of Srinivasan and Ruparel (1990).

CREDEX generally allows for the evaluation of the level of risk attached to the loan requested, while explaining its nature and taking into consideration the financial, economic, social and sectoraldata of the company. The CGX, on the other hand, allows for the prior development of a data andknowledge base adapted to support the client evaluation process in order to be able to subsequently develop the appropriate model to help determine credit limits.

More generally, the common objective for both systems is to help rating agencies and banks to assess the quality of companies applying for credit.

Dietsch and Petey (2003) summarized the advantages of expert systems in their ability to consistently reproduce expert decision rules in terms of credit and default risk assessment system (Dietsch & Petey, 2003) since they are based on expert experience and are subject to post-hoc validation. They are qualitative in nature, but incorporate quantitative standards (Sadi, 2010) by taking into consideration the contextual parameter without requiring the availability of historical data, which gives them a clear advantage over scoring methods.

However, it should be noted that expert systems are not without their limitations. They are subject to a great deal of human subjectivity, insofar as the judgments of the most influential experts in the financial community are, generally, more appreciated than those of unknown experts. Also, the factremains that when a company is rated well by an expert system, it generally tends to perform betterthan a company with a lower rating (Sadi, 2010). Finally, insofar as expert systems rely on the experience of experts, it seems difficult to define scientific mechanisms for testing the results of these systems, whereas scoring or other models can be subjected to a wide range of statistical inferencetests (Sadi, 2010). As such, the commercial development of expert systems seems very limited and their application by banking and financial institutions remains very modest.

4.4. The external rating

The rating is an old technique in the United States which developed in France during the 1990s andin Morocco during the 2000s. According to Percie du Sert (1999), the rating is "a classic means ofinformation on the level of risk of an issuer. It essentially concerns the risk of default by the borrower". (Percie du Sert, 1999). As such, and with the evolution of legal requirements and banking supervision, rating techniques have continued to evolve during the 1990s, especially with the first recommendations of the Basel Committee (1988). These recommendations detailed, in particular, the existing weightings while taking into consideration the external ratings carried out by the various rating agencies (Khlifa, 2017). The objective is to help financial organizations evaluate the credit risk of companies requesting financing while ensuring their financial soundnessand their risk of default. Generally, ratings are assigned by specialized, reputable and independentrating agencies, such as Standard and Poor's, Moody's, etc. Each agency uses its own rating scale,relying essentially on score models, while putting in

place a procedure for collecting information and financial diagnosis, at the request of the issuing company. The latter is generally at the origin of the rating request, in return for a fee paid to the rating agency. The company is then involved inthe procedure insofar as it is obliged to provide the rating agency with all the necessary internal information.

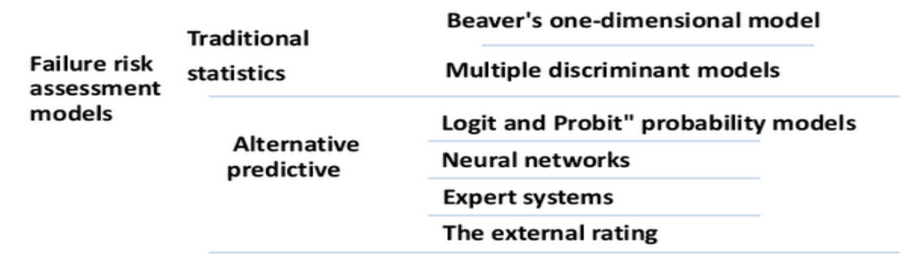
The rating (score) assigned to it is widely disseminated and during the entire life of the issue, the rating agency ensures a rigorous monitoring of the company (the borrower) which may lead to a re-evaluation of the rating with a positive or negative outlook (Barmaki, 2005).

More concretely, thanks to the scores produced, rating models allow borrowers to be arranged into risk classes within a coherent framework. Any score assigned will therefore provide information on the risk of default. Low scores indicate a high probability of default. High scores indicate low default risks. Equal or identical scores indicate similar risk levels (Brédart, 2015). Financial institutions generally pay close attention to these scores when deciding whether to grantcredit to a company or an industry. The more favorable the score, the better their confidence in thecompany or sector. It should also be noted that any company can generally oppose the publicationof a score that is not consistent with the image it wishes to convey. In fact, when the rating issuedby the rating agency reflects an unfavourable opinion on its ability to repay, it provides information aimed at improving the security of other investors by engaging its total responsibility towards them. However, as long as the financial organization uses its own predictive models of default, as mentioned above, it is only responsible to itself. Therefore, it is commonly accepted that internal risk assessment models and external rating systems can only be complementary rather than substitutes (Barmaki, 2005).

Also, it is worth adding that with the latest Basel II recommendations, the legal use of external ratings has been extended to a real institutionalization of rating agencies on the one hand and to a real implementation of new regulations impacting particularly SMEs on the other hand. As a result,the various financial organizations are called upon, more than ever, to be more and more committed, to rigorously evaluate the future capacity of each borrower, by adopting, jointly, an internal and external rating system (Khlifa, 2017).

This being the case, and in view of the panoply of rating techniques and predictive models of corporate default proposed, there is no universal consensus on the best statistical or probabilistic model or rating formula to adopt. Thus, the majority of authors agree on the importance of the choice of the methodology to adopt and on the rigorous and preliminary examination of the predictive capacity of any model to be applied.

Figure 3 : Synthetic presentation of the main models for assessing the risk of failure



Source : Authors

5. Conclusion

For more than fifty years, business failure has been the subject of several theoretical and empiricalworks that aimed, mainly, at proposing models for predicting failure, identifying its causes and/orunderstanding the processes leading to its demise (Bloch, et al., 1995). More concretely, the examination of these research works has shown that the theme of business failure can only be approached in a rigorous way by crossing the various disciplines and approaches (Brédart, 2015). It is thus and through this research work that we highlighted the complexity of this phenomenon via the various types of contributions which were developed in this direction and particularly, those relating to the forecast of this phenomenon by trying through a certain number of methods to evaluate the risk of failure using indicators, mainly, financial offering a static sight classifying the companies in "failing or healthy" companies. This being the case, the majority of authors agreethat only a dynamic, multidisciplinary and global approach highlighting the why and how of failurewill allow us to understand, explain and consequently forecast this phenomenon.

Also, it is important to specify that the inventory of the various works cited above has allowed us to consider that the set of failure models developed in this sense sought, mainly, to determine the best adapted method to predict the state of the companies by calling upon various more or less sophisticated tools (scoring models, discriminant analysis, etc.) (Brédart & Séverin, 2021). However, the fact remains that none of these models is either perfect or robust. Each one has its shortcomings and constraints and is subject to one or more limitations, despite the development ofnew techniques inspired by the functioning of the human brain, based on artificial intelligence andintegrating qualitative variables that are more explanatory of the failure, such as algorithms, neuralnetworks, expert systems, etc.

More globally, it is important to conclude that each predictive model of default has its advantagesand limitations and that the efficiency of each model depends, primarily, on the specifics of each economy, the methodology adopted by the researcher, and the explanatory variables used to buildthese models (Kovacova, et al. 2019; Zizi, et al., 2021). As a result, proper consideration of these parameters remainsa primary necessity before the adoption or design of any predictive model.

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