FAILURE AND VALUE CREATION: A DISCRIMINANT ANALYSIS APPLIED TO MOROCCAN INDUSTRIAL COMPANIES LISTED ON THE CASABLANCA STOCK EXCHANGE

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Abstract. This article purposes to assess the contribution of shareholder value creation as an explanatory variable for the failure of Moroccan industrial companies listed on the Casablanca stock exchange. It also offers a scoring that reflects the probabilities of the financial difficulties to occur. There were used data for 30 Moroccan industrial companies listed on the Casablanca stock exchange during the period of study from 2010 to 2018. Methodologically, a linear discriminant analysis was employed. The empirical results of the discriminant analysis applied during the period of 2010-2018 show that value creation, liquidity and the size of the company are the most determining variables in classifying companies according to the degree of financial difficulties. Thus, the results received make it possible to create a relationship among recurrent scientific knowledge about forecasting the companies’ failure and empirical findings in the context of Moroccan industrial companies listed on the Casablanca stock exchange.

Keywords: value creation, failure, scoring, discriminant analysis

JEL Classification: C38, G32, G33

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1. Introduction

During the 21st century, we have witnessed the failure of large companies such as Parmalat in Europe, Enron, and WorldCom in the United States. The Moroccan context was not spared insofar as many firms listed on the Casablanca stock exchange were the subject of legal proceedings, of which Moroccan public limited company of the refining industry remains the most publicized.

The occurrence of such a phenomenon as failure is not without repercussions. Often related to an open system, organized, and interconnected with its environment, the company represents a knot of contracts among various stakeholders whose breach through default impacts their wealth creation potentials. Business owners agree to bear the risk associated with doing business in return for random compensation. They rank last in terms of seniority and risk total or partial non-compensation during liquidation.

The imperative to predict corporate failure then arises while considering the interests of shareholders. In this sense, scoring is a failure prediction tool based on the statistical processing of financial data highlighting the different aspects of financial difficulties. Therefore, our research applies to answer the following question: to what extent do the levels of value creation allow explanation and prediction of the failure of Moroccan industrial companies listed on the Casablanca stock exchange?

This problem can be broken down into three research questions: - What are the most explanatory failure determinants of Moroccan industrial companies listed on the Casablanca stock exchange? - Is there a direct causal link between the creation of shareholder value and default? - What is the likelihood of the failure of Moroccan industrial companies listed on the Casablanca stock exchange?

Our paper examines the contribution of shareholder value creation as an explanatory indicator for the failure of Moroccan industrial companies listed on the Casablanca stock exchange. It also offers a scoring that reflects the probabilities of the financial difficulties to occur. There were employed data for 30 Moroccan industrial companies listed on the Casablanca stock exchange in the period of study from 2010 to 2018. The empirical findings of the discriminant analysis indicate that value creation, liquidity and the size of the company are the most influential indicators in classifying companies according to the degree of financial difficulties. Thus, our results make it possible to reveal a nexus between recurrent scientific knowledge about forecasting the failure of firms and empirical results in the case of Moroccan industrial firms listed on the Casablanca stock exchange. The strictly financial approach focused on forecasting default offers partial understanding of the default nature. Besides, the financial ratios are founded on accounting and financial information, the credibility and informational content of which may be called into question. Reasons why introducing strategic and organizational indicators as well as adopting the IFRS standard would add value in predicting a failure.
To provide the answers, the second section reviews the literature on value creation and business failure. The third section is devoted to presenting the methodology applied, to the statistical analysis as well as to interpreting the results. Finally, section 4 outlines the conclusions of the research.

2. Literature Review

Prediction of a failure has long attracted the interest of many researchers both academically and professionally. This research is part of the anticipation of the failure occurrence and the measurement of its likelihood. However, it is distinguished by the approach adopted to apprehend the failure as well as the context studied. As such, it should be recalled that prediction of the failure of Moroccan companies listed on the Casablanca stock exchange is insufficiently researched since the majority of studies on financial difficulties relate to companies not registered on the Casablanca coast (Taouab, 2014; Kherrazi & Ahsina, 2016; El-Ansari & Benabdellah, 2017).

Theoretical approaches and measures linking value creation to default have developed within two main theories which are agency theory and stakeholder theory, which will be presented below. This will allow further explaining the main measures of failure.

2.1. The Problem of Value Creation in the Corporate Financial Theory

The first proposal to define the concept of value in finance was initiated by Williams (1938), who considers the value of a financial asset by the present value of the future financial flows that it secretes.

As for creating the value, it represents a dogma that has been developed in the United States advocating that leaders must maximize the value of the company owners’ actions. Prosaically, the capital mobilized by a company generates profitability which must be relativized to the cost of financing. We speak of value creation when "the capital left in the business by the donors brings in more than what it costs". It corresponds to the rent that shareholders receive beyond their opportunity cost by which they are usually paid (Charreaux & Desbrières, 1998).

The creation of shareholder value is the main purpose of a business to exist. The latter constitutes a constellation of interests whose dissent by default impacts the creation of shareholder wealth due to the costs of bankruptcy (Warner, 1977). Unlike other creditors, shareholders bear the risks relating to the company’s activity and uncertainty that characterizes their remuneration.

In addition, the business owners, who represent residual creditors, are on the top notch of priority in terms of repayment, insofar as they would not be returned until the debts of the other claimants have been settled. As a result, shareholders could risk not being compensated in the event of the company bankruptcy in financial difficulty. Therefore, the creation of shareholder value must be considered in predicting failure.
2.1.1. Value Creation in the Agency Theory

Even though the focus of the agency theory is on the conflict of interests between the shareholder and the manager, it managed, over the course of these consecutive developments, to shed important light on the shared role of the manager and of the shareholder in creating shareholder value.

Thus, the shareholder being a contributor of funds is assimilated to a lender since he hopes for a remuneration of the funds made available to the firm in the form of return on investment. He is the agent (or the principal) if we use the terms of the agency theory (shareholders / managers relationship).

Still referring to the agency theory, executives use discretionary margins to maximize their interests at the expense of those of shareholders, which is what drives agency costs. They are also responsible for decisions that go against projects with high value creation.

Control over the manager is therefore essential to avoid his spoliator behavior. Jensen (1989) proposes debt as an appropriate control mechanism to reduce the discretion of managers and force them to act in the interest of shareholders. Other theorists, notably Shleifer & Vishny (1986), Bethel & Liebeskind (1993) and Agrawal & Knoeber (1996), propose the notion of capital concentration as a guarantee of effective control over the directors by the shareholders in addition to indebtedness.

Indeed, in a firm with a dispersed shareholding, no shareholder can bear the cost of a control over the management of the directors, while the benefit of this action will benefit the rest of the shareholders. On the other hand, when a shareholder alone has the largest share of the capital, he will be encouraged to invest in controlling the management of the firm, since he will appropriate a non-negligible share of profits from this action.

2.1.2. Creating Value in the Stakeholder Theory

The stakeholder theory contrasts the models in which the shareholders have a central role (shareholder value) with the models presenting all the stakeholders of the company (stakeholder value). Indeed, the company is understood as a constellation of interests whose objective is to create value for various stakeholders. In addition, the manager becomes an agent of all stakeholders.

However, the partnership conception of the company systematically leads to the problem of wealth distribution. In this regard, Jensen (2002) argues that when you maximize the company value, and therefore that of its owners, you also create value for other stakeholders “leading, under certain reasonable conditions, to maximization of social well-being”. On the other hand, we find in the model of partnership governance that, using its own incentive levers, each stakeholder participates in creating value for the firm.
2.2. The Concept of Failure: Definition and Approaches

Historically, failure has always been associated with a problem of value creation. Thus, the failure corresponds to the company’s inability to generate positive added value, or to fulfill its economic objectives of maximizing value for its shareholders regularly. Failure is a term that reflects the reality that is difficult to grasp. Ambiguity that surrounds this phenomenon relates to the diversity of its mode of analysis since it is positioned at the center of several disciplines.

2.2.1. An Economic-Legal Definition

From a legal point of view, article 560 of the Moroccan commercial code considers default as the state from which legal proceedings are opened against a company. This procedure occurs when a company is in a state of insolvency, that is it is no longer able to cover its current liabilities with its available assets. This is a definition to be distinguished from the situation of companies in difficulty and which are liable to adjustments rather than to liquidations.

From a financial perspective, default is associated with the situation in which the company finds itself unable to honor its financial commitments at maturity vis-à-vis its creditors (Baldwin & Mason, 1983; Wruck, 1990) and is, therefore, unable to meet its current liabilities.

2.2.2. The Importance of Failure in the Literature

The importance of the economic and social fallout from such a phenomenon as default has aroused the interest of several studies as rich, but far from being analogous. In the first predictive approach, failure constitutes a field favorable for implementing statistical methods. By focusing on the analysis of financial information, this perspective aims at distinguishing between failing companies and those that are not by detecting the financial and accounting symptoms warning of “a situation of failure” and by measuring its likelihood through the use of statistical techniques (Dimitras et al., 1996).

Although the financial approach to default in its strict-sense certainly leads to understanding the financial mechanisms that lead a company to bankruptcy, it remains limiting, because it offers a static and short-term perception, de facto, does not allow a full apprehension of failure. Such arguments justify the evolution of research from a predictive perspective to an explanatory approach which emphasizes identification of the root causes of failure, their overlaps (Hambrick & D’Aveni, 1992; Sheppard, 1994) and the modeling of the sequential trajectory that a company can take to fulfill the legal conditions for the cessation of payment (Laitinen, 1991; Ooghe & De Prijcker, 2008).

Finally, it is important to note that business failures in Morocco register a significant increase each year. In 2017, 8,045 companies were declared to be in default, maintaining an upward trend of 16% per year since 2009, while the figure was only 1,700 cases in 2007.
3. Methods

The construction of a scoring model capable of predicting failure in listed Moroccan companies helps the company and its various partners make decisions at the right time. On the one hand, it would allow leaders to detect the failure by means of its manifestation and intervene in it by preventive measures. On the other hand, it would provide the opportunity to guide shareholders' choices in allocating their resources. In addition, it helps break the information gap between the company and the other stakeholders (bankers, auditors, investors, etc.).

The methodology applied consists in establishing a statistical link among the meticulously chosen explanatory variables, including those of value creation, and the trichotomous modality which characterizes the companies in our sample through a discriminant analysis.

We will start with a presentation of the methodological diagram of our study (explanatory and explained variables, presentation of the sample as well as the hypotheses of the model) before explaining the results obtained and their interpretation.

3.1. A Methodological Approach

The methodology applied consists in studying the Moroccan industrial companies listed on the Casablanca stock exchange between 2010 and 2018. The sample is made up of the industrial companies as representative as possible of the profiles considered of financial difficulty. Subsequently, there will be collected the data from the financial communications of companies available on the site of the Casablanca stock exchange, the site of the Moroccan capital market authority (MCMA) as well as the annual reports of the ethics committee on securities (ECS).

For each observation, there will be calculated the financial ratios and indicators that represent the explanatory variables of our model. Based on the average data, there will be established a discriminant analysis in its descriptive and probabilistic approach using the SPSS software to identify the most discriminating factors and estimate the probability of the occurrence of financial difficulties.

The results obtained will be examined in the light of the existing literature on business failure.

3.2. Formalization of the Model

To establish a relation among the financial situation \( Y \) and the \( p \) financial indicators and ratios of companies \( X_1, ..., X_p \), we will use a linear discriminant analysis. It is a statistical method which highlights the links between a qualitative endogenous variable and a set of quantitative variables. On the one hand, it makes it possible to identify the linear combination of latent variables explaining the failure which are selected sequentially according to their discriminating power. In addition, it makes it possible to calculate the score of the observations which express the degree of difficulty of the companies as a function of the
For a sample made up of \( k \) groups, the model resulting from the linear discriminant analysis takes the following form (Desbois, 2003):

\[
S_j = a_{1j}X_1 + a_{2j}X_2 + a_{3j}X_3 + \cdots + a_{pj}X_p + a_{0j}
\] (1)

Where, \( a_{ij} \) represent the coefficients of the \( i \)th discriminating variables of the \( j \)th discriminating function, \( a_{0j} \) is a constant of the \( j \)th discriminating function.

On the other hand, the Bayesian approach to a discriminant analysis consists in estimating the probability of conditionally belonging to the discriminating variables and assigning them to the most likely group. Under the assumption of the variables’ normality and the homogeneity of the variance - covariance matrices, this so-called apostolic probability is estimated by the Bayes formula according to the a priori probability of belonging to the different groups.

The adoption of this method is preferred over others since the estimation of the discriminant function coefficients is not affected by the mode of selecting observations. On the other hand, scoring models built based on conditional probability methods, logit and probit, provide inconsistent and biased estimates of the constant and all the coefficients because of the sample selection method. In addition, binary logistic regression allows testing a regression model whose explained variable is dichotomous (Zmijewski, 1984), which is not the case in our article.

### 3.3. Model Variables

Our research focuses on analyzing financial difficulties, oriented towards vulnerability and precariousness, since this allows real understanding of the failure and gives more legitimacy for forecasting. In the absence of a conventional definition of financial difficulties, a review of the literature relating to predicting financial difficulty made it possible to identify the qualifiers that characterize precarious enterprises and which form the basis of our study, namely:

- Decrease in equity and debt restructuring (Pastena & Ruland, 1986).
- Non-distribution or reduction of dividends (De Angelo & De Angelo, 1990).
- A low coverage ratio (Asquith et al., 1994).
- Debt restructuring and disposal of assets (John et al., 1992).
- The downward change in stock prices and a negative operating result (Gilson et al., 1990).
- Cessation of payment and liquidation which allude to financial fragility in its extreme stage.
Thus, the variable “financial difficulties” is incorporated into the model as an explained variable according to the following coding: it takes the value 0 when the observed business is healthy, the value 1 for fragile businesses and the value 2 for companies extremely vulnerable.

Regarding the explanatory variables, we select a battery of $p = 21$ indicators capable of highlighting the degree of difficulty as well as the ability of companies to create value. The choice of variables is supported by their recurrence in previous work relating to the forecast of default (Bellovary et al., 2007), their relevance in financial analysis as well as theoretical and practical considerations. As shown in Table 1, these indicators are broken down into four headings: financial structure, liquidity analysis, systemic risk and size of companies, and value creation indicators.

Table 1. Explanatory Variables Used for the Empirical Study

| Heading                          | Ratios                        | Formula                                                                 | Code |
|----------------------------------|-------------------------------|-------------------------------------------------------------------------|------|
| **Structure ratios**             | Gearing                       | Financing debts / Equity                                                | $X_1$|
|                                  | Level of Equity               | Equity / Total liabilities                                             | $X_2$|
|                                  | Repayment capacity            | Financing debts / Self-financing capacity                              | $X_3$|
|                                  | Coverage ratio                | Gross operating surplus / Financial expenses                          | $X_5$|
|                                  | Capital intensity             | Fixed assets / Total assets                                            | $X_6$|
| **Liquidity ratios**             | General liquidity             | [Current assets + Assets Cash] / [Current liabilities + Liabilities cash]| $X_7$|
|                                  | Reduced liquidity             | [Current assets excluding stocks + Assets Cash] / [Current liabilities + Liabilities cash] | $X_8$|
|                                  | Immediate liquidity           | [Assets Cash] / [Current liabilities + Liabilities cash]              | $X_9$|
| **Value creation indicators**    | Economic Value Added (EVA)    | [net operating profit after tax (NOPAT)]n − [weighted average cost of capital (WACC) * Invested Capital (IC)] | $X_{10}$|
|                                  | Cash-Flow Return on Investment| Gross operating surplus / Employed capital                            | $X_{11}$|
|                                  | Return on Equity              | Net profit / Equity                                                   | $X_{12}$|
|                                  | Return on Capital Employed    | [Operating result * (1-T)] / Economic Assets                           | $X_{13}$|
|                                  | Return on Assets              | Net profit / Total assets                                              | $X_{14}$|
|                                  | Pay Out Ratio                 | Dividends / Net profit                                                | $X_{15}$|
|                                  | Dividend yield                | Unit dividend / Share price                                            | $X_{16}$|
| **Stock market indicators**      | Market Value Added            | $\sum_{t=1}^{\infty} \frac{EVA_t}{(1 + k)^t}$                         | $X_{17}$|
|                                  | Total Shareholder’s Return    | $\log([P_t – Unit dividend) / P_{t-1}])$                              | $X_{18}$|
|                                  | Market to Book Ratio          | Market capitalization / Equity                                        | $X_{19}$|
|                                  | Systemic risk                | $\text{COV}(r_i, r_m) / \text{VAR}(r_m)$                             | $X_{20}$|
|                                  | Size of companies             | $\log(\text{Total assets})$                                           | $X_{21}$|

Note: $T$ indicates Tax rate, $k$ indicates Cost of capital, $t$ indicates time in years, $P_t$ and $P_{t-1}$ indicate the Share price at time $t$ and $t-1$ respectively, $\log$ indicates the Logarithm, $\text{COV}$ indicates the covariance, $\text{VAR}$ indicates the variance, $r_i$ indicates the investment $i$ return and $r_m$ indicates the market return.

Source: developed by the author.
creation. It should be noted that shareholder wealth has often been measured by traditional variables to predict failure. Where appropriate, these measures will be supplemented with indicators that reflect the fundamental idea of creating shareholder value, namely Economic Value Added (EVA) and Market Value Added (MVA).

3.4. Selection of the Sample

Realization of this study leads to sampling the Moroccan industrial companies listed on the Casablanca stock exchange according to the following motivations:
- This typology of companies is subject to the shareholders’ impulses and requirements and those of investors in terms of value creation.
- They are subject to the legal and regulatory obligation of financial communication. Access to the various data is then docile.
- They provide a volume of data necessary to constitute the subgroup of businesses in precarious situations and those that are not.
- Restricting the sample to industrial companies helps remedy the bias relating to the sector of activity.

In this study, there are adopted the sampling procedure by Platt & Platt (2008). The choice of companies will be non-random, insofar as the companies will be classified a priori to a category according to at least three criteria among the six conditions used to define the difficulty of the companies. Following a careful selection process, and opting for the trichotomy classification by Altman et al. (1994), the learning sample will consist of 30 companies broken down into three groups:
- The first group: made up of 7 healthy companies.
- The second group: composed of 18 financially fragile firms.
- The third group: which includes 5 extremely vulnerable companies, 2 of which have been delisted from the stock market due to financial difficulties and one company subject to judicial liquidation.

3.5. A Research Hypotheses

We seek to verify the contribution of the various financial ratios and indicators introduced as independent variables ($X_1; ..., X_{21}$) in the explanation of the variable "difficulty of companies" considered as dependent variable (Y). Consequently, it follows from the modeling of the hypotheses to be verified in the light of the results obtained.

H1: "Insufficient liquidity is positively correlated with the likelihood of financial distress"
As suggested by Altman et al. (1977), high liquidity indicates a lower probability of default risk and that persistent liquidity problems result in an inability to honor long-term commitments or to cover operating cycle expenses.

H2: "The destruction of value would lead the company to financial difficulties"
Among the causes of financial difficulties, the most mentioned in the financial literature is the destruction of value or its instability. According to Taffler (1982), Keasey & Mc Guinness (1990) and many others, firms in financial distress generate insufficient profitability to compensate the factors of production.

In addition, they fail to leverage shareholder contributions and meet their dividend requirements (Gentry et al., 1985; Pompe & Bilderbeek, 2005). Beaver (1968) and Aharony et al. (1980) attest to their share that the more the possibility of default increases, the more the creation of the market value deteriorates.

H3: "The larger the size of a company is, the less it is exposed to financial difficulties"

The size of companies is a determinant of financial difficulties (Ohlson, 1980, Bredart, 2014). This fact can be explained in several ways. Generally, large companies have considerable ability to compete. In particular, the size of the company gives it a great deal of influence in terms of negotiation to appropriate the resources necessary for its survival in a competitive environment.

4. Results and Discussion

A discriminant analysis is a multidimensional statistical technique which aims at explaining the belonging of an observation to a predefined class representing a modality of a dependent variable, through detecting discriminating descriptors (variables). This essentially analytical procedure consists in seeking linear combinations of descriptors which allow, on the one hand, classifying the observations via a geometric criterion (factorial analysis), and on the other hand, optimizing the classification and to qualify it via probabilistic measures (a Bayesian analysis).

4.1. A Univariate Data Analysis

To differentiate between business classes, the analysis of descriptive statistics of each factor on each business category is fruitful. In addition, the analysis of variance provides a set of statistical tests to determine the variables that maximize discrimination between groups of businesses.

4.1.1. Data Descriptions

The discriminant analysis is concerned with identifying the variables that mismatch between companies according to the categorization used. In this sense, it seems interesting to establish a univariate descriptive analysis of the data within each class and to focus attention on the mean and the standard deviation. Examination of the descriptive statistics for each variable illustrated in Table II shows that the factors X1, X2, X7, X8, X9, X13, X11, X12, X18, X16, X15 and X21 have different means with relatively low dispersion within each class. As a first observation, these variables are discriminating given their ability to configure companies into groups that are both dislocated and homogeneous.

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Identify the variables that significantly discriminate over the three classes.

between groups, statistical units into homogeneous classes while breaking up with each other. To consolidate possible to establish an arbitration between two simultaneous points of focus: agglutinate the Leaning on the

Table 2. Means and Standard Deviations (given in brackets) of Financial Factors by Class of Affiliation

| Effective | Membership classes | Global |
|-----------|--------------------|--------|
|           | Healthy 7          | Fragile 18 | Failures 5 | 30     |
| X_1       | 0.181 (0.190)      | 0.172 (0.195) | 5.65460 (11.795) | 1.08770 (4.851) |
| X_2       | 0.750 (0.500)      | 0.503 (0.177) | 0.10820 (0.0646) | 0.494 (0.335)     |
| X_3       | 0.750 (0.766)      | 1.183 (1.563) | -0.44580 (7.173) | 0.810 (3.002)     |
| X_4       | 1.435 (2.071)      | 8.403 (12.392)| -1.77280 (18.089)| 5.081 (12.417)    |
| X_5       | 94.334 (71.532)    | 77.139 (124.832)| 2.45040 (3.401) | 68.703 (105.616)  |
| X_6       | 1.280 (1.717)      | 0.979 (2.194) | 0.2496 (0.185)   | 0.927 (1.887)     |
| X_7       | 3.061 (2.686)      | 1.711 (0.808) | 0.72400 (0.239)  | 1.86 (1.571)      |
| X_8       | 2.526 (2.553)      | 1.255 (0.764) | 0.52020 (0.200)  | 1.429 (1.465)     |
| X_9       | 0.352 (0.241)      | 0.103 (0.113) | 0.01860 (0.017)  | 0.147 (0.184)     |
| X_{10}    | -30.6 10^6 (34.6 10^6) | -9.3 10^6 (129.1 10^6) | -474.4 10^6 (979.3 10^6) | -91.8 10^6 (415.5 10^6) |
| X_{11}    | 0.068 (0.107)      | 0.045 (0.122) | -0.74240 (1.295) | -0.081 (0.577)    |
| X_{12}    | 0.269 (0.113)      | 0.155 (0.086) | -0.94860 (1.884) | -0.002 (0.827)    |
| X_{13}    | 0.211 (0.093)      | 0.197 (0.211) | -0.04260 (0.085) | 0.160 (0.194)     |
| X_{14}    | 0.250 (0.186)      | 0.167 (0.410) | -0.01440 (0.030) | 0.156 (0.336)     |
| X_{15}    | 0.965 (0.375)      | 0.719 (0.626) | 0.08920 (0.149)  | 0.672 (0.585)     |
| X_{16}    | 0.095 (0.08)       | 0.035 (0.016) | 0.000120 (0.002) | 0.043 (0.05)      |
| X_{17}    | -16.2 10^6 (37.9 10^6) | -5.8 10^6 (102.9 10^6) | -330.3 10^6 (710.1 10^6) | -62.3 10^6 (30.2 10^6) |
| X_{18}    | -0.196 (0.126)     | -0.159 (0.101) | -2.52540 (3.915) | -0.5622 (1.709)   |
| X_{19}    | 3.670 (2.423)      | 3.957 (4.301) | 1.99520 (3.206)  | 3.563 (3.741)     |
| X_{20}    | 0.035 (0.029)      | 0.029 (0.024) | 0.000660 (0.0149) | 0.0264 (0.025)    |
| X_{21}    | 9.027 (0.519)      | 9.057 (0.502) | 6.47600 (3.256)  | 8.620 (1.618)     |

Source: developed by the author.

4.1.2. Individual Discriminating Powers of Variables

Leaning on the variance decomposition, there will be selected the variables which make it possible to establish an arbitration between two simultaneous points of focus: agglutinate the statistical units into homogeneous classes while breaking up with each other. To consolidate the descriptive finding and therefore identify the variables that significantly discriminate between groups, there was tested, through the F test, the equality of each variable means over the three classes.

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Table 3. Equality Tests for Group Means

| Variables | Lambda of Wilks | F       | Signification |
|-----------|-----------------|---------|---------------|
| X₉***     | 0.578           | 9.848   | 0.001         |
| X₁₆***    | 0.601           | 8.958   | 0.001         |
| X₂***     | 0.630           | 7.916   | 0.002         |
| X₂₁***    | 0.637           | 7.707   | 0.002         |
| X₁₂**     | 0.726           | 5.101   | 0.013         |
| X₁₈**     | 0.727           | 5.071   | 0.014         |
| X₁₃**     | 0.728           | 5.048   | 0.014         |
| X₇**      | 0.763           | 4.190   | 0.026         |
| X₁₅**     | 0.764           | 4.160   | 0.027         |
| X₁₃**     | 0.772           | 3.997   | 0.030         |
| X₆**      | 0.790           | 3.596   | 0.041         |
| X₁*       | 0.817           | 3.031   | 0.065         |
| X₁₀*      | 0.824           | 2.881   | 0.073         |
| X₁₇*      | 0.836           | 2.641   | 0.090         |
| X₀         | 0.864           | 2.116   | 0.140         |
| X₄         | 0.882           | 1.802   | 0.184         |
| X₅         | 0.914           | 1.271   | 0.297         |
| X₁₄        | 0.936           | 0.924   | 0.409         |
| X₃         | 0.960           | 0.560   | 0.578         |
| X₁₉        | 0.963           | 0.524   | 0.598         |
| X₆         | 0.969           | 0.436   | 0.651         |

Note: ***. Significant discrimination at the 1% level, **. Significant discrimination at the 5% level, and *. Significant discrimination at the 10% level.
Source: developed by the author.

Table 3 shows Wilks' Lambda, the values of the F statistic (ratio between the mean of the intergroup square deviations and the intragroup square deviations) and the levels of significance of the F test corresponding to each variable. Variables are classified by an increasing level of their discriminating powers. Thus, variables X₉, X₁₆, X₂ and X₂₁ are strongly discriminating (significance level 1%), the equality of each variable means over the three classes is significantly rejected, which explains a visible arrangement of companies in different classes. Simultaneously, variables X₁₂, X₁₈, X₁₁, X₇, X₁₅ and X₁₃ are discriminating (significance level 5%) and variables X₆, X₁, X₁₀ and X₁₇ are weakly discriminating (significance level 10%). Indeed, the intraclass variance of these variables is very low compared to the interclass variance.
Thus, we deduce that the factors are the most explanatory $X_9$, $X_{16}$, $X_2$, $X_{21}$, $X_{12}$, $X_{18}$, $X_{11}$, $X_7$, $X_{15}$, $X_{23}$, $X_{18}$, $X_1$, $X_{10}$ and $X_{17}$ of the classification of enterprises and, therefore, they are determinants of business failure.

4.2. A Discriminant Analysis

4.2.1. The Discriminating Functions

In order to identify the mutual discriminating power of the variables (a multivariate problem) and to optimize the successive selection of the explanatory variables which maximize the distinction among groups of companies, we resort to a stepwise discriminant analysis based on the F-statistic. Given their large number, the explanatory variables risk expressing redundant information due to the presence of multicollinearity. To resolve this problem, the SPSS software performs a tolerance test when launching the discriminant analysis protocol. This step is used to resolve the problem of multicollinearity.

At the end of the sixth step, we have arrived at the discriminant functions which incorporate the linear combinations of descriptors associated with the estimated coefficients and which maximize the distinction among groups of companies:

\[
S_1 = 6.262X_1 + 0.863X_9 + 2.953X_{10} + 8.847X_{18} - 0.208X_{16} + 3.871X_{21}
\]
\[
S_2 = 0.577X_1 - 0.711X_9 + 0.348X_{10} + 0.875X_{18} - 0.724X_{16} + 0.366X_{21}
\]

Furthermore, the contribution of linear combinations of the discriminating variables is interpreted through analyzing the structure matrix (Table 4). This makes it possible, through the coefficients of factorial structure, to determine the intragroup correlation of the variables constituting the model and the discriminant functions.

It should be noted that value creation, manifested by the variables TSR ($X_{18}$), the dividend yield ($X_{16}$) and EVA ($X_{10}$), is preeminent in the classification of firms. Indeed, there is a causal link of default and creation of value, since the firms which do not make their committed capital profitable and those which fail to meet the shareholders’ requirements in terms of value creation are the most exposed to failure. This leads to a deterioration in the rate of return on corporate shares (Taffler, 1982; Keasey & Mc Guinness, 1990; Pompe & Belderbeek, 2005; Beaver, 1968; Aharony et al., 1980). In addition, they distribute dividends proportional to the market value of low stocks compared to healthy companies (Gentry et al., 1985). With reference to our result, hypothesis 2 is validated.

In addition, it can be seen that size ($X_{21}$) is predominant in discriminating between companies. Our finding converges with those by Ohlson (1980) and Bredart (2014) who attest that the larger the business is, the more it can absorb the various hazards and difficulties that hinder its normal progress. Thus, hypothesis 3 is validated.
Table 4. The Structure Matrix

| Variables | Discriminating functions |   |   |
|-----------|--------------------------|---|---|
|           |                          | 1 | 2 |
| $X_{15}$  | 0.404*                   |   | -0.163 |
| $X_{13}$  | 0.316*                   |   | -0.179 |
| $X_{14}$  | 0.309*                   |   | 0.097 |
| $X_{6}$   | 0.283*                   |   | 0.258 |
| $X_{5}$   | 0.202*                   |   | -0.090 |
| $X_{6}$   | 0.135*                   |   | 0.115 |
| $X_{21}$  | 0.108*                   |   | 0.042 |
| $X_{11}$  | 0.098*                   |   | 0.034 |
| $X_{19}$  | 0.089*                   |   | 0.004 |
| $X_{18}$  | 0.087*                   |   | 0.037 |
| $X_{12}$  | 0.085*                   |   | -0.003 |
| $X_{1}$   | -0.068*                  |   | -0.022 |
| $X_{10}$  | 0.066*                   |   | 0.043 |
| $X_{17}$  | 0.065*                   |   | 0.047 |
| $X_{9}$   | 0.064                    |   | -0.710* |
| $X_{16}$  | 0.074                    |   | -0.614* |
| $X_{5}$   | -0.008                   |   | -0.455* |
| $X_{8}$   | 0.077                    |   | -0.383* |
| $X_{20}$  | -0.113                   |   | 0.272* |
| $X_{4}$   | 0.016                    |   | 0.228* |
| $X_{2}$   | -0.011                   |   | 0.186* |

Note: (*) A greater absolute correlation between each variable and any discriminant function. (a) This variable is not used in the analysis.

Source: developed by the author.

In addition, immediate liquidity ($X_{9}$) is significant in the distinction among various business classes in accordance with the results by Altman et al. (1977). These authors claim that failing businesses are characterized by their inability to service their short-term debts. Indeed, our result leads to the validation of hypothesis 1.

4.2.2. A Discriminating Power of Functions

Implementation of the discriminant analysis by the SPSS software gives the decreasing classification of the score functions according to their discriminant power as well as the eigenvalue associated with each.
Table 5. Eigenvalues and Canonical Correlations

| Function | Own value | % of variance | Canonical correlation |
|----------|-----------|---------------|----------------------|
| 1        | 49.090    | 97.9          | 0.990                |
| 2        | 1.042     | 2.1           | 0.714                |

Source: developed by the author.

Table 5 shows, on the one hand, that the first discriminating function explains most of the intergroup variance up to 97.9%. However, the second function only explains 2.1% of the intergroup variance. On the other hand, the coefficient of the canonical correlation of the first evaluated function of 0.990 is quite close to 1. Consequently, there is a strong correlation between the first discriminating function and the explained variable translating class membership. This reflects a considerable discriminating ability, particularly for the first discriminating function.

In addition, Wilks' lambda statistics measures the power of the linear combination of discriminating variables to be discerned among statistical units. It represents the complement of the correlation ratio to reach the total variance, the smaller the statistic, the more discriminating the variables.

| Test of the function (s) | Wilks Lambda | Chi-square (ddl) | Signification |
|--------------------------|--------------|-----------------|---------------|
| From 1 to 2              | 0.010        | 113,376 (12)    | 0.000         |
| 2                        | 0.490        | 17,487 (5)      | 0.004         |

Source: developed by the author.

Table 6 shows that Wilks' lambda is 0.01 with a significance of the associated Chi-square test (Bartlett transformation) significantly less than 1%, which reflects that the variables retained by the analysis are globally discriminating. In addition, it shows that the Wilks lambda of the second discriminating function (0.49) is significantly weak at 1% which shows that the two functions are significantly discriminating and consequently they are both adoptable in the model.

4.2.3. A Geometric Assignment Rule

The discriminating functions constitute the axes which define the space on which the companies will be projected according to their factorial coordinates (the scores of the companies valued through the discriminating functions). The planned assignment class will be the one whose scores are closest to the group’s barycenter’s (Table 7). Thus, the three assignment regions are delimited by two border lines constructed based on the Mahanalobis-Fisher geometric assignment rule.
Table 7. Barycentres of the Groups

| Initial membership | Function 1 | Function 2 |
|--------------------|------------|------------|
| Healthy            | 3,490      | -1,680     |
| Fragile            | 2,767      | 0,680      |
| Failed             | -14,848    | -0,096     |

Source: developed by the author.

4.2.4. A Bayesian Assignment Rule

The discriminating Bayesian analysis consists in estimating the probabilities of companies’ belonging conditionally to the descriptors and assigning them to the most probable group. Soliciting the probabilistic approach to a discriminant analysis requires the adoption of two stochastic hypotheses, notably the multi-normality of the explanatory variables and the homoscedasticity of their variance-covariance matrices. Table 8 illustrates a classification of companies expressed in terms of expected probability of belonging according to their degree of failure corrected by the level of value creation.

It should be noted that the companies’ classification according to the Bayesian approach adds a subtlety and lucidity to the geometric approach for anticipating the financial health of firms, insofar as it provides the probability of belonging to different groups in a nuanced way. Hence there is the establishment of a staggered border between them.

Table 8. Assigning Companies to Groups, Probabilities, and Scores (the three assignment errors are noted in bold italics)

| Company | Initial assignment | Planned assignment | Probability of group assignment | Discriminating scores |
|---------|-------------------|--------------------|---------------------------------|-----------------------|
|         |                   |                    | Healthy | Fragile | Failed | Fct. 1 | Fct. 2 |
| N°9     | Healthy           | Healthy            | 0.99953 | 0.00047 | 0.000 | 3.920 | -3.902 |
| N°11    | Healthy           | Healthy            | 0.99511 | 0.00489 | 0.000 | 3.396 | -3.070 |
| N°17    | Healthy           | Healthy            | 0.99482 | 0.00518 | 0.000 | 3.849 | -2.907 |
| N°5     | Healthy           | Healthy            | 0.77188 | 0.22812 | 0.000 | 3.422 | -1.326 |
| N°19    | Healthy           | Healthy            | 0.61016 | 0.38984 | 0.000 | 3.520 | -0.969 |
| **N°4** | **Fragile**       | **Healthy**        | **0.56151** | **0.43849** | **0.000** | **2.810** | **-1.102** |
| N°28    | Fragile           | Fragile            | 0.00127 | 0.99873 | 0.000 | 2.024 | 1.586 |
| N°22    | Fragile           | Fragile            | 0.00173 | 0.99827 | 0.000 | 0.376 | 0.951 |
| N°12    | Fragile           | Fragile            | 0.00180 | 0.99820 | 0.000 | 0.360 | 0.930 |
| N°24    | Fragile           | Fragile            | 0.00358 | 0.99642 | 0.000 | 2.132 | 1.179 |
4.2.5. The Model Validation

4.2.5.1. The Rate of Good Rankings

After having developed the scoring model, it is necessary to validate the model by calculating the well-classified rates. These rates calculated based on the learning sample itself are resubstituting rates, and they overestimate the real rates of well-classified. To overcome this estimation bias, we use cross validation, which consists in classifying each unit by the discriminant functions derived from all the other units (apart from it). The results of validation by resubstituting and those of cross-validation are illustrated in Table 9.

| N°   | Type   | Status | Good | Bad | Resubstituting | Cross-Validation |
|------|--------|--------|------|-----|----------------|-----------------|
| N°6  | Fragile| Fragile| 0.00678 | 0.99322 | 0.00 | 2.582 | 1.046 |
| N°8  | Fragile| Fragile| 0.00731 | 0.99269 | 0.00 | 3.695 | 1.354 |
| N°14 | Fragile| Fragile| 0.00924 | 0.99076 | 0.00 | 2.790 | 0.984 |
| N°18 | Fragile| Fragile| 0.01096 | 0.98904 | 0.00 | 2.893 | 0.935 |
| N°15 | Fragile| Fragile| 0.01486 | 0.98514 | 0.00 | 2.237 | 0.604 |
| N°4  | Fragile| Fragile| 0.01677 | 0.98323 | 0.00 | 3.620 | 0.975 |
| N°21 | Healthy| Fragile| 0.03572 | 0.96428 | 0.00 | 3.231 | 0.560 |
| N°10 | Fragile| Fragile| 0.04317 | 0.95683 | 0.00 | 4.872 | 0.946 |
| N°22 | Healthy| Fragile| 0.13073 | 0.86927 | 0.00 | 3.176 | -0.082 |
| N°21 | Fragile| Fragile| 0.21109 | 0.78891 | 0.00 | 2.903 | -0.410 |
| N°18 | Fragile| Fragile| 0.37347 | 0.62653 | 0.00 | 1.329 | -1.231 |
| N°26 | Failed | Failed | 0.000 | 0.000 | 1 | -14.52 | -0.302 |
| N°30 | Failed | Failed | 0.000 | 0.000 | 1 | -14.71 | 0.055 |
| N°27 | Failed | Failed | 0.000 | 0.000 | 1 | -14.81 | 0.184 |
| N°25 | Failed | Failed | 0.000 | 0.000 | 1 | -15.19 | -0.234 |

Source: developed by the author.
Table 9. The Percentage of Well-Classified (Confusion Matrix)

| Type                     | Initial class | Planned class |
|--------------------------|---------------|---------------|
|                          |               | Healthy       | Fragile       | Failed |
| Validation by            | Healthy       | 5             | 71.4%         | 2      | 28.6% | 0     | 100%  |
| resubstitution           | Fragile       | 1             | 95.6%         | 0      | 4.4%  | 0     | 100%  |
|                          | Failed        | 0             | 0.0%          | 0      | 0.0%  | 5     | 100%  |
| Cross validation         | Healthy       | 4             | 57.1%         | 3      | 42.9% | 0     | 100%  |
|                          | Fragile       | 2             | 11.1%         | 16     | 88.9% | 0     | 100%  |
|                          | Failed        | 0             | 0.0%          | 1      | 20.0% | 4     | 100%  |

Source: developed by the author.

Note that the rate of the good classification in the group of failing companies is perfect (100%). However, the overall rate of the good classification is up to 80% \([(4 + 16 + 4)/30]\). This shows that the failure is particularly well identified by the model adopted, and that, in addition, the discriminating power of this model is generally confirmed.

4.2.5.2. A Multi-Normality Test

The Bayesian discriminant analysis assumes that the explanatory factors must be multi-normally distributed. The degree of flattening and multivariate asymmetry is two simple and informative parameters and provide information about the normality of the data distribution. To test this hypothesis, we will use the Srivastava multi-normality test which shows that the data distribution does not follow a multinormal law. The rejection of this hypothesis is justified by the existence of extreme values which bias the means and the standard deviations.

4.2.5.3. A Homoscedasticity Test

Homoscedasticity constitutes a hypothesis which stipulates that the variance-covariance matrices are equal within each class constituting the learning population. To examine the homogeneity of the variance-covariance matrices, a Box's M test will be used.

Table 10. Box M test

| M of Box | 403,469 |
|----------|---------|
| $F_{ddl1}$ | 10,980 |
| $F_{ddl2}$ | 490,483 |
| Signification | 0.000 |

Source: own elaboration.

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Table 10 displays the test result showing an M of Box equal to 403.47 which at a level of significance is lower than 1%. Indeed, the hypothesis of homogeneity of the variance-covariance matrices is refuted. Failure to comply with this assumption is due to the lack of balance among the sizes of business classes.

Furthermore, and despite the violation of probabilistic assumptions, it is necessary to validate the results of the discriminant analysis: in fact, the classification error rate; rather weak; is an infallible criterion in the adoption of the model (Eisenbeis, 1977).

5. Conclusions

In this research, we have concluded that value creation, liquidity and the companies’ size explain the failure of Moroccan industrial companies listed on the Casablanca stock exchange. Thus, our results make it possible to establish a link between recurrent scientific knowledge about forecasting the companies’ failure and empirical findings in the context of Moroccan industrial companies listed on the Casablanca stock exchange.

However, the results obtained cannot overshadow the gaps associated with it. In the first order, the selected sample is divided into disproportionate classes, which affects the comparability among companies with the incompleteness of certain information. To resolve this problem, it is advisable to further extend the research horizon or to widen the study sample by integrating commercial companies or service providers while considering sector specificities.

Second, the use of a discriminant analysis imposes restrictive theoretical conditions, including the extent to which non-compliance with the hypotheses of multi-normality of the explanatory variables and homogeneity of the variance-variance matrices influences the sharpness of the model. The use of logistic regression is an interesting avenue of research because it tolerates such conditions. In addition, implementation of the two methods makes it possible to compare their quality of discrimination.

Third, the strictly financial approach focused on predicting default provides limited understanding of the default nature. In addition, the financial ratios are calculated based on accounting and financial information, the credibility and informational content of which may be called into question. Reasons why the introduction of strategic and organizational variables as well as the adoption of the IFRS standard would add value in predicting failure.

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