# Testing Sherrod and Springate Models in Predicting Financial Distress: The Case of Some Algerian Companies

**Amine SABEK***

University of Tamanghasset, Algeria

*sabek.amine@univ-tam.dz*

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**Abstract :**

The objective of this research is to utilize the Springate and Sherrod models in analyzing the Aurassi and Saidal companies over the span of 2015 to 2019. This analysis aims to evaluate their predictive accuracy and understand how their structure interacts within the Algerian context. Especially since these models have been well received by previous researchers. The findings of the study show consistent outcomes aligning with both models, yet the (Sherrod) model exhibited greater precision and specificity compared to the (Springate) model.

***Key Words:*** Financial Distress, Prediction, Springate, Sherrod.

**JEL Classification**: G33, C53.

* Corresponding author: Amine Sabek (*sabek.amine@univ-tam.dz*)

## Introduction:

Financial Distress Prediction is a priority for firm that intend to reduce its potential losses, and seeks to achieve a stable financial base capable of facing various financial risks. Financial distress leads to negative effects on firm financial structure. Especially, since the effects are not limited to the economic aspect only, extending to reduce continuity probabilities. In addition, the exposure of large number of firms to financial distress at the same time leads to a severe crisis in the economic capital, which puts the future of the specific country in critical situation, pushing to empty the treasury to assist the distressed firms.

Predicting financial distress is significant topic that has been extensively searched. However, there is a constant need for deeper research, especially given the presence of several surrounding aspects that need more attention. Given the continuous increase in the number of distressed companies, it was imperative to employ statistical models depend on real-world data. The relevent models seek to transform initial data into valuable results to identify the real financial status of the firms.

The main research question can be formulated in the following:

**How effective are the Sherrod and Springate models in predicting financial distress in Algerian companies?**

The study presents several hypotheses. It is worth mentioning that the validity of the hypotheses will be verified in the results of study:

- **H1**: Aurassi is a healthy firm.
- **H2**: Saidal is is a distressed firm.
- **H3**: The results of Sherrod are more accurate than the Springate model.

In this study, the initial data was extracted from the real-world companies. This is related to "Aurassi Hotel Management", and "Pharmaceutical Industry Saidal". The limited data, is a result of the difficulty of obtaining financial statements of Algerian companies. We compensated for this by expanding the time scope of the research from 2015 to 2019.

The study provides several objectives. Firstly, it aims to present practical application to stakeholders who seek workable approaches of mitigating financial losses and ensuring business continuity. Secondly, this research seeks to assess the accuracy of such prediction models across dissimilar industrial sectors in Algeria.

The selected companies are from diversified industries, which enhances the relevance of the study through inferences about the flexibility and reliability of both the Sherrod and Springate models. This approach will further the understanding not only of financial distress but also of developing selective strategies for improved economic resilience.

The following sections provide a critical review of the literature on predicting financial distress, with an emphasis on explaining the statistical bases of both the Sherrod and Springate models. In its application section, these models have been empirically tested using financial data derived from Algerian companies. This is followed by discussion of the findings and the main aspects. Finally, the final sections present the main research findings, describe the results of hypothesis testing, and provide recommendations for further development in financial forecasting.

## I. Literature review:

Financial distress is a situation where a firm undergoes financial stress or deteriorating financial health, a situation also referred to as business or corporate failure (El-Bannany et al, 2020, p 170). Dun & Bradstreet, the major provider of pertinent statistics on failed businesses, defined business failure as businesses that go out of business following bankruptcy or assignments with losses to voluntary withdrawal, and creditors, leaving court actions, or unpaid obligations (Zhou & Elhag, 2007, p 301). Financial distress is the status of a firm characterized by low cash flow in which deadweight losses are incurred but are not technically insolvent (Panigrahi, 2019, p 65). In that respect, financial distress could also be understood as the last stage of decline for an organization before bankruptcy. In that light, therefore, financial distress contrasts with bankruptcy in that it represents a time frame in which the borrower cannot afford to repay a loan obligation to lenders (Puro, 2019, p3). Bankruptcy is only one of several outcomes related to financial distress; it is more of a legal term than an economic one (Pindado & Rodrigues, 2005, p 344). Many would describe business failure as bankruptcy, but a firm is not legally bankrupt unless its governing law so states it (Mayliza, 2020, p 170).

Predictive approches first came in the mid-1960s. Beaver (1966) had applied a single variable analysis to predict credit risk by assuming critical cut-off values for particular return, solvency variables, and liquidity. The first to predict bankruptcy using multiple discriminant analysis was Altman (1968), with his Z-score model. This model turned out to be better in the prediction perspective than the univariate models. Ohlson (1980) introduced Logistic Regression (LR) into business failure prediction. Thereafter, the popularity of LR became rampant and today is generally considered as one of the most widely used techniques in business failure prediction in the world.

The aforementioned is the actual beginning of the process of predicting financial risks using statistical models. Further, after that, different nationality researchers competed with each other according to the different place and time of the study in trying to enhance the quality of prediction the financial risks. Gerantonis et al (2009) tested whether the Z-score models can be used to predict bankruptcy even two and three years before its occurrence. Indeed, as revealed by the study, the Altman model is very effective at predicting distress. Husein & Pambekti (2014), also managed to prove that the models developed by Altman, Zmijewski, Springate, and Grover can also be used for the purpose of predicting financial distress. However, among others, the Zmijewski model is the best in predicting financial distress because the level of its significance is the highest. Arkan (2015) tested the strength of the B-Sherrod model for the purposes of detecting financial distress, which will enable investors and other concerned users to visualize the going concern ability of a firm. By applying the Sherrod model, Babela & Renas (2016) discovered that bankruptcy risk exposure in the selected banks is very low, while banks listed on the Iraqi Stock Exchange cannot depend on the Kida model because its results do not correspond to the banking sector. Elviani et al (2020) proved that both Springate

and Altman models had the best accuracy in predicting bankruptcy of trade sector firms in Indonesia. Medjoub & Houas (2020) proved that Kida model is the best in terms of predicting the failure of companies listed on ASE. The study showed the failure of Altman and Sherrod models in predicting distress.

Sabek & Saihi (2021) applied Back-propagationa type of Artificial Neural Network (ANN), the Back-propagationa in predicting the financial distress of 10 Algerian firms and proved that this type of network is very suitable. Muzanni Yuliana (2021) proved that in predicting bankruptcy in Indonesian retail companies, the Zmijewski model was the most accurate. Sabek (2023) compared two different variants of ANN models with LR, in order to prove that not every type of ANN models outranks LR. Sabek & Horak (2023) have done some tuning of hyperparameters of Gaussian Process Regression with the purpose of finding the best model for financial distress predicting. Sabek & Saihi (2023) compared LR with ANN on the financial distress predicting of Algerian and Saudi Arabian of companies. Rainarli & Sabek (2023) applied some preliminary methods, including downsampling and replacing missing feature values by the mean of neighboring data points to handle issues of dataset balancing and missing data. Sabek (2024) compared CA Score, Kida and Springate models in finding out the best model in predicting financial distress in Algeria. Sabek et al (2024) tested the using First-Order Autonomous Learning Multi-Model to predict Bankruptcy.

Formula of Sherrod model's is as follows: (Abu Orabi, 2014, p 33)

$$Z = 17X_1 + 9X_2 + 3.5X_3 + 20X_4 + 1.2X_5 + 0.10X_6$$

While:

$X_1$ = Working capital / total assets ;

$X_2$ = cash assets / total assets ;

$X_3$ = total shareholders' equity / total assets ;

$X_4$ = earnings before interest and taxes / total assets ;

$X_5$ = total assets / total liabilities ;

$X_6$ = total shareholders' equity / tangible fixed assets.

As the value of (Z) increases, it shows that the financial standing of the company is strong and therefore the company has a very good chance to continue. On the other hand, when the value of (Z) decreases, it shows the financial risks facing the company to continue (Arkan, 2015, p 241).

Formula of Springate model's is as follows: (Primasari, 2017, p 29)

$$S = 1{,}03X_1 + 3{,}07X_2 + 0.66X_3 + 0{,}4X_4$$

While:

$X_1$ = Working capital ratio / total assets ;

$X_2$ = Ratio of income before interest and tax on total assets ;

$X_3$ = The ratio of income before tax / total current debt ;

$X_4$ = The ratio of sales / total assets.

According to Springate, the company with a value of S > 0.0862 is classified as a healthy company. On the other hand, companies with an S value < 0.862 are classified as potentially bankrupt.

## II. Examination of the Financial Distress Prediction Models:

In this study, the initial data was extracted from the real-world companies, listed in the Algerian Stock Exchange. This is related to the "Aurassi Hotel Management", and the "Pharmaceutical Industry Saidal". The limited data, is a result of the difficulty of obtaining financial statements of Algerian companies. We compensated for this by expanding the time scope of the research (2015-2019). Table 1 shows the results of applying the Sherrod model on Aurassi.

**Table 1: Sherrod results - Aurassi**

| Statement | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| **$X_1$** | 0.196 | 0.161 | 0.170 | 0.129 | 0.153 |
| **$X_2$** | 0.133 | 0.108 | 0.105 | 0.067 | 0.065 |
| **$X_3$** | 0.382 | 0.392 | 0.421 | 0.436 | -0.066 |
| **$X_4$** | 0.061 | 0.034 | 0.057 | 0.048 | -0.025 |
| **$X_5$** | 1 | 1 | 1 | 1 | 1.064 |
| **$X_6$** | 0.647 | 0.601 | 0.670 | 0.735 | -0.083 |
| **Z** | 8.350 | 7.021 | 7.715 | 6.555 | 3.723 |

**Source**: By author.

Table 1 shows that Z values are generally confined between $-5 \geq Z \geq 20$. This indicates that the Aurassi, according to Sherrod model, went through two different statuses through two phases. The first one spanned 5 years from 2015-2018, where the 2016 is the point of the Z value return to the bottom, to settle in 2018 at a value of 6.555. Although Z-value in this period was characterized by instability, the difference between its values was not significant. The second phase spanned only one year 2019, where the Z value decreased by nearly double, as it became confined between $-5 \geq Z \geq 5$.

Thus, the company fell into the fourth level, and it can be noted that the Aurassi at this stage indicates more exposure to financial distress than bankruptcy. Note that financial distress is a stage that precedes bankruptcy but does not necessarily lead to it, especially in the case of rectify the situation. Table 2 shows the results of applying the Sherrod model on Saidal.

**Table 2. Sherrod results - Saidal**

| Statement | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| $X_1$ | 0.357 | 0.181 | 0.160 | 0.200 | 0.184 |
| $X_2$ | 0.171 | 0.110 | 0.104 | 0.079 | 0.047 |
| $X_3$ | 0.586 | 0.592 | 0.616 | 0.500 | 0.538 |
| $X_4$ | 0.041 | 0.045 | 0.032 | 0.031 | 0.020 |
| $X_5$ | 1 | 1 | 1 | 1 | 1 |
| $X_6$ | 2.681 | 2.011 | 2.027 | 2.280 | 1.286 |
| Z | 11.947 | 8.440 | 7.854 | 7.909 | 7.162 |

**Source**: By author.

Table 2 shows that the financial situation of Saidal is completely different, as the company went through one status, and the Z-value was confined between $5 \geq Z \geq 20$, and this indicates the difficulty of predicting bankruptcy according to Sherrod model. Table 3 shows the results of applying the Springate model on the "Aurassi".

**Table 3. Springate results - Aurassi**

| Statement | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| $X_1$ | 0.219 | 0.171 | 0.185 | 0.151 | 0.154 |
| $X_2$ | 0.073 | 0.046 | 0.069 | 0.072 | -0.025 |
| $X_3$ | 0.568 | 0.272 | 0.479 | 0.368 | -0.574 |
| $X_4$ | 0.266 | 0.241 | 0.265 | 0.280 | 0.116 |
| S | 0.930 | 0.593 | 0.824 | 0.731 | -0.253 |

**Source**: By author.

Table 3 that Saidal went through three phases according to the S-value. The first phade included only one year 2015, where the S-value was far from the bankruptcy probability according to Springate standards. S-value in this period exceeded the minimum risk set at 0.862, which indicates that the company is healthy.

Whereas the second phase started from 2016 to 2018, when this period witnessed turmoil confirmed by the noticeable decline in the S-value, so that the company's position returned again to the existence of a medium probability of bankruptcy in 2016, especially since the S-value significantly decreased from its predecessor in 2015, which confirms that the company suffers from confusion. The situation improved in 2017.The third stage concerned with the year 2019, this period shows a great collapse in value according to Sherrod model, in which the firm was classified within the fourth level, which indicates the existence of bankruptcy possibility, and this was confirmed by Springate model. Table 4 shows the results of applying Springate model on Saidal.

**Table 4. Springate results - Saidal**

| Statement | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| $X_1$ | 0.465 | 0.284 | 0.259 | 0.338 | 0.244 |
| $X_2$ | 0.053 | 0.070 | 0.052 | 0.055 | 0.032 |
| $X_3$ | 0.216 | 0.278 | 0.209 | 0.182 | 0.130 |
| $X_4$ | 0.372 | 0.354 | 0.345 | 0.452 | 0.342 |
| S | 0.933 | 0.832 | 0.702 | 0.817 | 0.572 |

**Source**: By author.

Table 4 shows that the S-value for the first year 2015 exceeded the minimum risk estimated at 0.862, which indicates that the company was healthy. The same result according to Sherrod's model.

Although the Z values indicate financial stability, they are in a continuous decline that can lead to bankruptcy over time, which was confirmed by Springate model, which indicates that it may suffers from a financial distress in 2016, but the firm did not deal with, and this allowed it to develop in subsequent years, which gradually affected on the level of financial performance. Table 5 evaluate Sherrod results.

**Table 5. The predictive accuracy of Sherrod model**

| Observed | | Predicted | | |
|---|---|---|---|---|
| | | Y | | % Correct |
| | | 0 | 1 | |
| Actual Y | 0 | 1 | 1 | 50 |
| | 1 | 0 | 8 | 100 |
| Overall % | | | | 90 |

**Source**: By author.

Table 5 shows that Sherrod model was able to correctly identify (8) cases of non-distress cases, and (1) case of financial distress. Otherwise, it was unable to correctly identify (1) case of financial distress. Table 6 evaluate Springate results .

**Table 6. The predictive accuracy of Springate model**

| Observed | | Predicted | | |
|---|---|---|---|---|
| | | Y | | % Correct |
| | | 0 | 1 | |
| Actual Y | 0 | 2 | 0 | 100 |
| | 1 | 6 | 2 | 25 |
| Overall % | | | | 40 |

**Source**: By author.

Table 6 shows that Springate was able to correctly identify (2) non-distress cases, and unable to correctly identify (6) non-distress cases. Moreover, it was able to correctly identify (2) cases of financial distress without error.

## Discussion

According to Sherrod model, Aurassi went through two different statuses through two phases. The first one spanned 4 years from 2015 to 2018. The Z values during this phase generally confined between $-5 \geq Z \geq 20$. The second phase, which in turn spanned only one year 2019, where the Z value decreased by nearly double, as it became confined between $-5 \geq Z \geq 5$. According to Springate model, the Aurassi has experienced a financial distress in 2017, and due to the slight profitability in this period, it prompted the company to record a large loss in 2019, which confirms that it failed to maintain its continuity as a result of successive financial failures.

Although Saidal maintained the third category in all years of study according to Sherrod model, this does not make it immune from the bankruptcy risk, especially since the Z-value continued to decline gradually and continuously, starting from 2015 to 2019. This indicates that Saidal is in continuous deterioration. According to Springate model, the second phase started from 2016, in which the company was classified as at risk of bankruptcy with varying degrees, but the year 2019 was the most dangerous, which confirms that the firm was definitely exposed to financial failures in previous period. Sherrod model achieved suitable results with a classification accuracy of 90%. Otherwise, Springate model achieved unfavorable results with a classification accuracy of 40%, which is completely unacceptable, given its reputation.

## Conclusions

The findings of this research would provide the expected addition to the Algerian academic research field, assisting the relevent companies to uncover their financial imbalances and determine their financial status. The most important of which are.

- According to results, and on the contrary of Aurassi, Saidal is considered a healthy company, indicating the financial soundness in most years. This was confirmed by the two models. This makes both of **H1** and **H2** incorrect.
- The continuous deterioration in value indicates the existence of imbalance that leads Saidal to a critical situation over time. This is what has been observed in post-2016.
- Sherrod model' results were more accurate and specific. This makes the **H3** correct.
- Both models' results emphasize the presence of imbalances in the financial structure of Aurassi, especially in the year 2019.
- The causes of the financial imbalance of Aurassi in 2019 are very clear without reaching the values of S or Z, in view of the negative value of the relevent financial ratios.

## Recommendations

The research provide several recommendations as follows:

- Recommending the model of Sherrod in the first place in terms of classification accuracy. Besides, testing it with larger dataset.
- It is necessary for the financial management of Aurassi to deal with the occurred deterioration during 2019, examining its reasons, in an attempt to provide effective solutions.
- The two models agreed on the existence of clear financial imbalances in the financial position of the “Aurassi", especially the year of 2019.
- The status of Saidal indicates financial healthy according to both models. Nevertheless, there is continuous decline in value, especially in the post-2016 period. It is necessary to identify the reasons, address the continuous decline, and provide solutions.

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