

# Predicting Financial Distress: Multi Scenarios Modeling Using Neural Network

Mohamed Sameh Gameel<sup>1</sup> & Khairy El-Geziry<sup>2</sup>

<sup>1</sup> Faculty of Business Administration, Sadat Academy for management sciences, Cairo, Egypt

<sup>2</sup> Faculty of Commerce, Cairo University, Giza, Egypt

Correspondence: Mohamed Sameh Gameel, Faculty of Business Administration, Sadat Academy for management sciences, Cairo, Egypt. Tel: 002-0100-648-1258. E-mail: mohamed.sameh@sadaacademy.edu.eg

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## Abstract

This paper aims to investigate the best scenario to predict financial distress in the Egyptian stock market using a neural network model. The sample consists of 37 company listed on the EGX100. The sample period is eight years from 2001 to 2008, so we can isolate the effects of global financial Depression in the end of 2008, and the effect of economic instability, which coincided with the Egyptian revolution in 2011 till now. The results show evidence that the best scenario for predicting distress in Egypt is that the company will be distressed if there is a decreasing in liquidity, decreasing in generating cash from sales with increasing in financial leverage.

**Keywords:** financial distress, neural network, multi scenarios, financial modeling, emerging markets

## 1. Introduction

Charitou et al. (2004) demonstrated that in the beginning of the financial forecasting modeling, there was not any sophisticated statistical methods or computers available to researchers. the first prediction way is to compare corporates financial ratios to each other and find if there is a clear difference in the ratios between the distressed and non-distressed firms.

In the 60's, researchers used statistical models to identify financial ratios that could classify companies into failure or non-failure groups. Beaver (1966) used a dichotomous classification test to identify the best financial ratios predict corporate failure. He used 30 financial ratios and 79 pairs of companies (failure/non-failure). The best ratio was the working capital/debt ratio, which correctly decremented 90 percent of the firms one year prior to failure. The second best ratio was the net income/total assets ratio, which correctly decremented 88 percent of the firms. There was a relatively few studies used the univariate model for distress prediction. Altman (1968) developed a multivariate statistical model to discriminate failure from non-failure firms. The initial sample was composed of 66 firms with 33 firms in each group. The financial ratios used in model were working capital/total assets, retained earnings/ total assets, earnings before interest and tax/total assets, market value of equity/ book value of total liabilities, and sales/total assets. The model was extremely accurate in classifying 95% of the total sample correctly one year prior to failure (-1 year), but misclassification of failed firms increased as the prediction time increased for prediction. Ohlson (1980) used the logit model to predict business failure with a sample of 105 failing firms and 2058 non-failing firms. The financial ratios included in the model were the firm size, total liabilities/total assets, working capital/total assets, current liabilities/current assets, a dummy variable indicating whether total assets were greater or less than total liabilities, net income/total assets, funds from operation/total liabilities, another dummy variable indicating whether net income was negative for the last two years and change of net income. The model did not perform as well as altman model. Mensah (1983) used multivariate discriminant analysis and logit analysis to develop models predict business failure, he intended to predict failure 2 to 5 years before it happens. The sample consisted of 11 financially distressed companies and 35 successful companies for the period 1975 to 1978. The financial ratios included in the model were the classified to eight groups of ratios as follow:

- Short-term Liquidity Ratios: Cash to Current Liabilities, Current Assets to Current Liabilities, Current Assets minus Inventories to Current Liabilities and Working Capital to Total Assets.
- Cash Flow Ratios: Cash Flow to Current Liabilities, Cash Flow to Sales, Cash Flow to Total Assets, Cash

Flow to Net Worth, Cash Flow to Total Liabilities and Cash Flow to Total Interest.

- Long-term Solvency Ratios: Net Worth to Total Liabilities, Net Worth to Long-term Liabilities, Net Worth to Total Assets, Net Worth to Fixed Assets and Net Operating Profit to Interest.
- Short-term Capital Productivity Ratios: Sales to Inventories, Sales to Accounts Receivable, Sales to Working Capital, Sales to Current Assets minus Inventories and Sales to Cash.
- Profit Margin Ratios: Net Operating Profit to Sales, Net Income to Sales and Interest to Net Income.
- Long-term Capital Productivity Ratios: Sales to Fixed Assets, Sales to Total Assets and Sales to Net Worth.
- Return on Investment Ratios: Net Income to Net Worth, Net Operating Profit to Total Assets, Net Operating Profit to Total Debt and Retained Earnings/Total Assets.
- Debt Coverage Ratios: Current Liabilities to Total Assets, Long-term Liabilities to Current Assets, Current plus Long-term Liabilities to Total Assets and Current plus Long-term Liabilities plus Preferred Stock to Total Assets.
- Price-Level Ratios: Business Income to Stockholders' Equity, Business Income to Total Liabilities, Business Income to Total Assets, Realized Gains/Losses to Total Assets and Realized Gains/Losses to Total Historical Cost Income.

The results showed that the percentage of error forecasting is 3.3% in the second year before failure. Zmijewski (1984) used the probit model to predict business failure with a sample of firms listed on NYSE between 1972 and 1978. The financial ratios included in the model were net income/total assets, total debt/total assets and current assets/current liabilities. Accuracy rate of Zmijewski's model was 95.29%. Lane et al. (1986) used the Cox model and discriminant analysis to predict bank failure with a sample of 130 banks that failed between January 1978 and June 1984, and 334 non-failed banks. The research classification based on the computation of the surviving probability of a bank more than 24 months, based on the values of financial ratios of the bank based on data from a prior year. The financial ratios included in the model were The log of the total capital/total assets, log of total loans/total capital, the log of sales of Treasury bills and purchases of securities/total assets, net recoveries of loans/total loans, the log of the loans/total operations expenses loss reserves, the log of the total cost of a loan/net income plus reserves for loan losses, the log of the commercial and industrial/total loans, real estate mortgage/total loans, loans interests/net loans, and total operations/total assets, net income/total assets, net income/total capital, net income/total operating income, total loans/total deposits, total loans/total assets, log of cash and securities/Total assets, log of domestic securities/total assets, and the log of purchases of Treasury bills and sales of securities/total assets. The results indicated that the overall accuracy of the Cox model was similar to the model using the discriminant analysis.

All approach includes discriminant analysis, regression analysis, logit analysis or probit analysis are usually requires that data follow certain assumptions, like data normally distributed to generate robust results (Beaver, 1966; Altman, 1968; Beaver, 1968; Deakin, 1972; Ohlson, 1980; Zmijewski, 1983; Platt & Platt, 1990; Theodossiou, 1991). Although financial data and ratios rarely have a normal distribution to be useful to make the models less sensitive to non-normal distributions.

In this research, we try to use neural network technique to avoid the assumption of the previous techniques, but we have a great problem with this technique due to the nature of financial distress. Financial distress is a complicated phenomenon needs many financial ratios to diagnose it, so with a large number of ratios the accuracy of the neural model deteriorated, as the dispersion of the data become bigger, so as a solution we built scenarios to predict financial distress. With multi-scenario modeling, the model can easily applied in different countries and different periods, as it has many scenarios can detect the financial distress phenomenon.

## 2. Description of Data and Sample

To predict financial distress, we use a sample of 37 companies listed on "EGX 100 index", the total observation is 259, 82 observation omitted as some data are missing, so 177 observation will be analyzed. The sample period is eight years from 2001 to 2008 to isolate the effects of global financial Depression in 2008, and the effect of economic instability, which coincided with the Egyptian revolution in 2011 tell now.

Table 1. Model variables

Ratio	symbol	Prior researchers
Net profit / total assets	Y1	Beaver, Deakin, Ohlson, Zavgren, Zmijewski, Casy, Lane, Theodossiou
Net profit / equity	Y2	Blum, Mensah
Net profit / sales	Y3	Mensah
Operational profit / sales	Y4	Mensah
Operational profit / total assets	Y5	Mensah, Lane
Current assets / current liabilities	Y6	Beaver, Deakin, Zmijewski, Casy, Mensah, Sharma
Net fixed assets / total assets	Y7	Platt
Inventory / current assets	Y8	
Cash / current liabilities	Y9	Deakin, Mansah, Norton
(current assets – inventory)/current liabilities	Y10	Deakin, Zavgren, Theodossiou, Edmister
Cash / total assets	Y11	Deakin, Zavgren, Norton, Casy
Current assets / total assets	Y12	Deakin, Norton, Casy
Inventory / total assets	Y13	Desheng
(current assets – inventory) / total assets	Y14	Deakin, Norton
Total liabilities / total assets	Y15	Mensah, Theodossiou, Platt
Current liabilities / total assets	Y16	Mensah
Long term liabilities / total assets	Y17	Beaver, Deakin
Operational profit / interest	Y18	Rushink
Equity / net fixed assets	Y19	Norton
Equity / total liabilities	Y20	Norton
Sales / inventory	Y21	Norton, Sharma, Mensah, Zavgren
Cash / sales	Y22	Deakin, Platt, Laitinen

### 3. Methodology

To build a predictive model we must first identify the distressed and non-distressed firms, then next analyze the firms with financial ratios, in order to use this ratios to build scenarios for predicting financial distress so the research divided into three main categories first identify the distress, second build scenarios and third predict using neural network

#### 3.1 Identify the Distress

To identify the distressed and non-distressed firms, we use altman Z-score estimated for non-manufacturers and emerging markets, Z-score model function is

$$Z = 6.56x1 + 3.26x2 + 6.72x3 + 1.05x4$$

Where

X1 = Working capital / total assets

X2 = Retained earnings / total assets

X3 = EBIT / total assets

X4 = Equity / total liabilities

The firm will be distressed if the score is between 1.1 and 2.6, and if the score is equal or more than 2.6 it will be a non-distressed firms. To distinguish between distressed and non-distressed firms for the neural network, we will use a dummy variable, the distressed firma will take value 1 and non-distressed firms will take value 0.

#### 3.2 Build Scenarios

In order to build the scenarios we use 22 financial ratio from the literature of finance as shown in table 1. In each year of the sample period, we will compute the ratios “y1, y2 y3, y4... y22” to build the model. Factor analysis will Use the previous y ratios to build the scenarios, which will mainly reduce the data dimensions and enhance the accuracy of the neural network, will use the weight of every ratio in each factor to determine the meaning of each factor as a probable scenario for distress.

#### 3.3 Predict Using Neural Network

Neural network will deal with the factors generated from the factor analysis, which will be the probable scenarios for distress, and then we will examined all this scenarios in the neural network to determine its

explanatory power. The type of the neural network that will be used is multilayer perceptron network, it will be trained by 72% of the total observations, and then network will be tasted with 19% of the total observation and tested the final model with 9 % of total observations. The network will be trained using two functions:

First function of processing layers is Hyperbolic tangent.

$$\gamma(c) = \tanh(c) = (e^c - e^{-c}) / (e^c + e^{-c}) \quad (1)$$

It takes real-valued arguments and transforms them to the range  $(-1, 1)$ , which suits the value of the factors, this is the activation function for all units in the hidden layers.

the second function of output layer (softmax function) is

$$\frac{e^{x_i}}{\sum_i e^{x_i}} \quad (2)$$

e: natural logarithm

x: input from the hidden layers

i: number of layer

The value of this function is the zero or one matches with the dummy variable of distress.

## 4. Results

### 4.1 Factor Analysis

factor analysis generates six factors, each factor is a scenario for financial distress, With revising the weight of each ratio in the factor in table 2, we can determining the mean of each scenario

#### 4.1.1 First Scenario

The company will be distressed if there is a decreasing in liquidity, decreasing in generating cash from sales with increasing in financial leverage

#### 4.1.2 Second Scenario

The company will be distressed if there is an increasing in debt and liabilities with decreasing in liquidity and equity, with decreasing in operational leverage.

#### 4.1.3 Third Scenario

The company will be distressed if there is a decreasing in liquidity and profitability appears in both return on asset and equity.

#### 4.1.4 Fourth Scenario

The company will be distressed if there is an increasing in inventory with decreasing in sales.

#### 4.1.5 Fifth Scenario

The company will be distressed if there is overinvestment in assets with financing from debt and long term loans.

#### 4.1.6 Sixth Scenario

The company will be distressed if there is a decreasing in operational leverage, sales and profitability.

Table 2. Rotated component factor matrixa

	Component					
	f1	f2	f3	f4	f5	f6
Y10	.883					
Y6	.858					
Y9	.839					
Y20	.832					
Y11	.641		.494			
Y16		.889				
Y14	.360	.887				
Y12		.876				
Y15		.669			.652	
Y19		.543				.358

Y4	.508	.404		.465
Y1		.894		
Y2		.887		
Y5		.886		
Y8			.901	
Y13	.401		.831	
Y21			-.492-	.396
Y17				.916
Y7				.697
Y3				.863
Y22	.365			.806

#### 4.2 Neural Network

After training the neural network, the network appears as the shown in Figure 1. We can see that the neural network have 12 processing layer with 2 output layers for the distress dummy variable.

Table 3 shows the accuracy of the final network is 100% in distinguish between distressed and non-distressed companies.

Table 4 shows the importance of each scenario in predicting financial distress, first scenario is the most important with 100% , then second scenario with importance of 75.9%, third scenario with importance of 75.9%, fourth scenario with importance of 64.3%, fifth scenario with importance of 36.5%, sixth scenario with importance of 47.4% for distress in Egypt. This meant that the first scenario is the most important and probable scenario for distress in the Egyptian stock market, which can refer to bad management for short term assets.

Table 3. Results of neural network

Sample	Observed	Predicted		Percent Correct
		0	1	
Training	0	64	0	100.0%
	1	0	64	100.0%
	Overall Percent	50.0%	50.0%	100.0%
Testing	0	15	1	93.8%
	1	0	17	100.0%
	Overall Percent	45.5%	54.5%	97.0%
Holdout	0	10	0	100.0%
	1	0	6	100.0%
	Overall Percent	62.5%	37.5%	100.0%

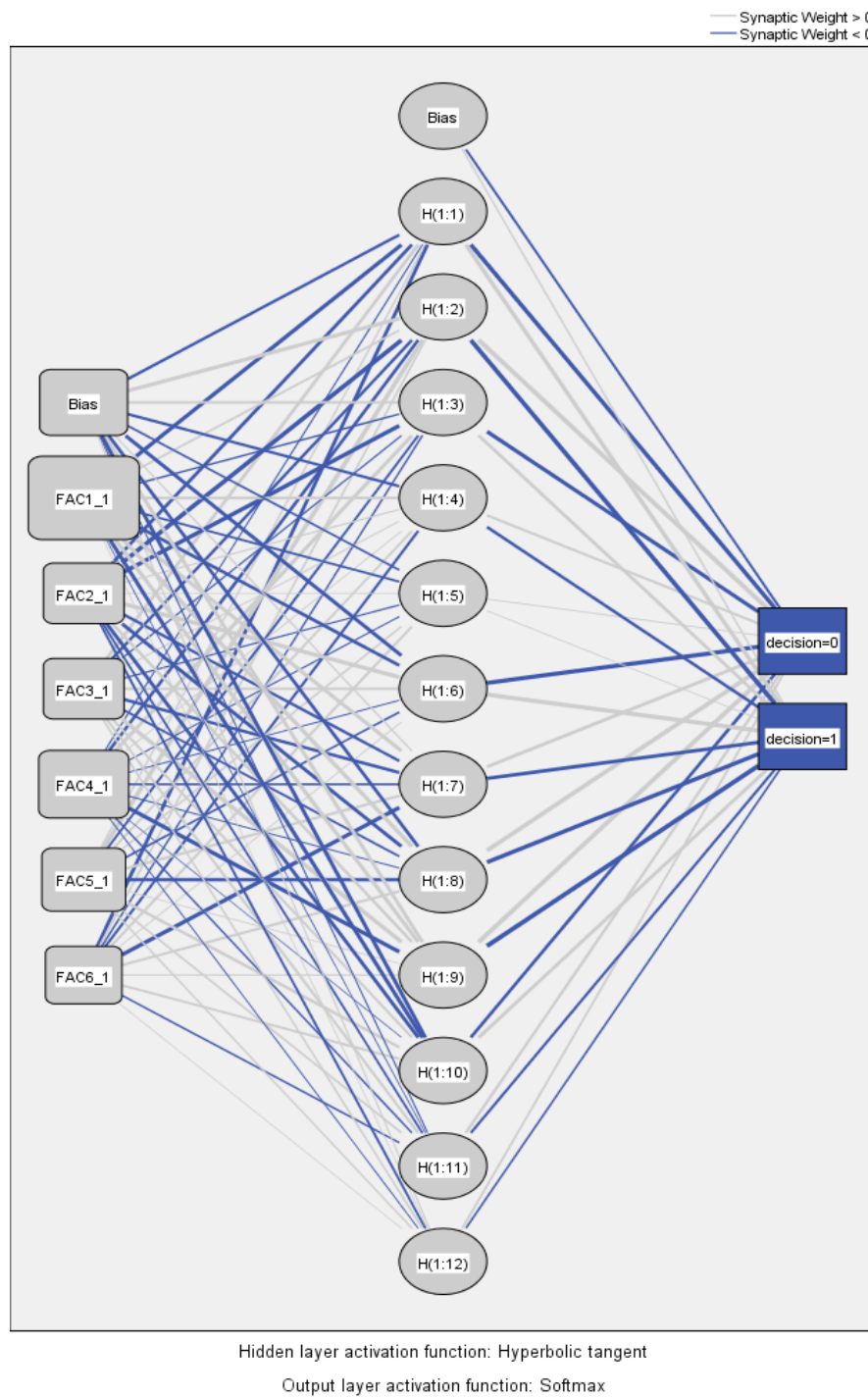


Figure 1. Multilayer perceptron neural network

Table 4. Importance of factors (scenarios)

	Importance	Normalized Importance
Factor 1	.253	100.0%
Factor 2	.192	75.9%
Factor 3	.181	71.5%
Factor 4	.163	64.3%
Factor 5	.092	36.5%
factor 6	.120	47.4%

## 5. Conclusion

The study tries to determine the best scenario to predict financial distress using neural network model. The results show evidence that the best scenario for predicting distress in Egypt is that the company will be distressed if there is a decreasing in liquidity, decreasing in generating cash from sales with increasing in financial leverage. The most important issue is that we can now use this model in different countries as it is a multi-scenario model, each country will have its own scenario, which will be one of the above scenarios. Researchers can use it and determine the most common scenario in his country, as these scenarios will determine the causes of distress, and help in avoiding the bad effects of distress.

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