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Predicting Financial Distress for Listed MENA Firms

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Abstract

Financial distress prediction gives an early warning about defaulting risk for firms; thus, it is a real concern of the entire economy.

Purpose: To examine the determinants of financial distress across MENA region countries, by using definitions of distress and historical data from active listed firms in the region.

Methodology: logistic regression is run on firm-specific variables and a set of macroeconomic variables to develop a prediction model to examine the effect of these predictors on the probability of financial distress.

Findings: it has been found that after controlling for country effects, accounting ratios, firm size, and macroeconomic variables provided an acceptable prediction model for listed MENA firms.

Originality: a gap exists in the literature of developing countries' prediction for financial distress. Many studies addressed bankruptcy prediction for a certain country in the region, however, a limited number of researches approached predicting distressed models for listed firms in the region.

Keywords: MENA, Financial distress, Prediction, Logistic regression, County effects

1. Introduction

The economic disorder, that has been emerging in almost every country in the Middle East and North Africa as a consequence of the 2008 global financial crisis and, more recently the so called "The Arab Awakening", has caused damage in the MENA region's capital markets, i.e. irritation of market liquidity, shortage in the accessibility of financial sources, falling in asset price, and deteriorating profits for firms. This has made it very difficult for the borrowers in the region to fulfill their debt obligations, (Hall *et al.,* 2013), (World Bank, 2015). This was accompanied by a sharp decline in commodity prices and a global liquidity shortage, "has pushed an increasing number of businesses into the position of financial uncertainty", (Hall *et al*., 2013).

Researchers examined the topic of business failure models in MENA countries, but most of the papers were about predicting bankruptcy for banks in the MENA regions, for example, (Distinguin *et al.,* 2010; Calice, 2014; Sahut & Mili, 2011), or predicting bankruptcy for one specific country in the region, (Al Khatib & Horani, 2012; Al Mansour, 2015; Moradi *et al*., 2013), or for a part of the region as in (Khoja *et al.,* 2016). No study till know, to our best knowledge, has developed financial distress model for listed companies in the MENA region, and this paper attempts to fill in this gap.

The lack of effective bankruptcy and insolvency laws has created an unstable environment for investment in MENA countries, (Belkhir, *et al*., 2016). Furthermore, for emerging economies, the complications in implementing bankruptcy legislation (Zikovic, 2017), and the unavailability of data, using active firms can be helpful and this leads to the adoption of theoretical financial distress definition.

Therefore, financial distress firms in this paper are defined as whenever the firm's financial expenses exceed its earnings before interest and taxes, depreciation and amortization (EBITD & A) for 2 consecutive years accompanied by a decline in its market value in these 2 years, (Pindado et al., 2008) and whenever the firm has negative EBIT for 2 consecutive years, (John et al., 1992).

The results obtained by running logistic regression on a set of variables from data extracted from ORBIS database, International Financial Statistics (IFS), and International Country Risk Guide website indicate that firm specific variables, size, measured by market capitalization, and macroeconomic factors, can predict financial distress for listed MENA firms, moreover, the results show that financial distress varies across countries in the region.

This study supports the literature on financial distress prediction in developing countries. The need for it is derived from the fact that financially distressed companies remain as a significant threat to the economy and growth, especially in disturbed area as in the Middle East and North Africa.

The introduction will be followed by Section 2 which presents the literature review. Section 3 refers to the data and the methodology employed. Section 4 presents the empirical results, and, Section 5 concludes the paper.

2. Literature Review

Different modeling techniques have been applied to business failure/financial distress prediction since the 1960's. These models can be classified into 3 main categories: "statistical models", "artificial intelligence models", and "theoretical models", (Aziz & Dar, 2006).

The first published statistical and mathematical models were in the 1960s, although the field started earlier (Gepp & Kumar, 2012). The first statistical business failure prediction model was presented by Beaver (1966). Beaver (1966) has evaluated the predictive ability of 30 variables using univariate discriminant analysis. He found that a single ratio can predict bankruptcy for firms up to 3 years before it occurs.

Several hidden problems arise from the simple univariate approach, and the most important one is the choice of the optimal cutoff point. The cutoff point is chosen when the company has been bankrupt, which indicates that it could be sample specific. On the other hand, the Company is classified based on one ratio at a time, this may give inconsistent classification results when using different ratios for the same company, besides the fact that one ratio cannot capture the complexity of a firm (Altman, 1968). The solution according to Altman (1968), is to select a collection of ratios, using Multiple Discriminant Analysis technique (MDA) to capture the complete representation of the firm.

Altman (1968) pioneered the use of MDA to business failure prediction. The Z-scoring model developed by Altman (1968) is then widely used. The classification accuracy of the Z-score model is 95%, and 83% one year and two years before the bankruptcy respectively. A following study conducted by Deakin (1972) that used quadratic MDA and 14 accounting ratios was used by Beaver (1966). The developed model can predict potential firm's failure up to 3 years before it occurs.

MDA is a widespread statistical method used to develop predictive models, and many researchers have used it, (Aziz & Dar, 2006). However, the assumptions of discriminant analysis made it hard to assess the developmental models (Zavgren, 1985). As a result, alternative modeling techniques that require fewer assumptions are needed.

Three models for predicting failure one, two and three years before bankruptcy were developed by Ohlson, (1980) who was the first to use the Logistic Regression Analysis in business failure prediction. The developed models could predict failure up to three years before failure and have demonstrated a prediction accuracy of 96% for both one year and two years preceding the failure.

Later, probit regression analysis has been used by Zmijewski, (1984), but it is not used frequently in business failure prediction literature as logistic regression since both models provide the same results, and logistic regression requires fewer assumptions than probit do (Walsh & Cunningham, 2016; Emel *et al.*, 2003; Balcaen & Ooghe, 2006).

Data Envelopment Analysis was used in the prediction literature in the late 1990s, (Emel et al, 2003). Emel et al (2003), applied DEA techniques to 82 manufacturing firms, using financial ratios, DEA combined the complete performance of the firm into one efficiency score, the “credibility score”, the accuracy of their model is 91%. When compared to the results obtained with those of regression and MDA, Emel et al (2003) found that the results are not significantly different.

On the other hand, Khalili Araghi and Makvandi (2012) found that the predictive power of DEA compared with Logit and Probit models in predicting corporate business failure for Iranian companies, is not encouraging. However, Mousavi et al., (2019) empirically proved that using DEA with the proper efficiency measures improves the performance of the prediction models.

According to Gepp & Kumar (2012), several authors such as Steyn-Bruwer and Hamman (2006), Arroyave (2018) confirmed that both classification accuracy for MDA and logistic regression are not significantly different.

In the early 1990s, another mainstream model in the literature of the business failure prediction model was employed, Artificial Intelligence methods, (Yu et al., 2014). Artificial Intelligence methods suffer from problems of strict assumptions, low prediction accuracy, poor generalization ability, and low learning rate, (Yu et al., 2014; Walsh & Cunningham, 2016). However, compared to logistic regression and multiple discriminant analysis, Artificial Intelligence models are still new and need more examination, (Kiyak & Labanauskaite, 2012).

The importance of predicting financial distress has been highlighted by numerous predicting literatures. In this regard, and based on the preference of the researchers, many criteria for classifying firms as financially distressed have been existed, (Pozzoli & Paolone, 2017).

Most of the literature on corporate failure models used the juridical definition, bankruptcy (Kingsley, *et al*., 2015; Balcaen & Ooghne, 2006), i.e. (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Khalili Araghi & Makvandi, 2012; Khoja et al., 2016), and many others.

Altman, (1968), recognized weakness in bankruptcy definition. He claimed that the firm samples are divided based on their status, whether bankrupt or not regardless of the fact that firms may suffer from temporary operational difficulties, and may not necessarily end up bankrupt.

Whereas, companies may declare bankruptcy for a variety of reasons, such as, “sudden bankruptcy” such as bankruptcy due to natural disasters, (Hill et al. 1996) or “accidental bankruptcy” (Davis and Huang2004), or due to an acquisition, merger, liquidation, or voluntary liquidation, etc., and not only because of bankruptcy, (Balcaen & Ooghe, 2006). However, the definition of failure varies depending on the local conditions of the country, and the preference of the researcher. Failure can be synonymous to the company filing for bankruptcy, defaulting on bond payment, liquidation, delisting from Capital Market, and, government intervention via special financing, (Altman & Narayanan, 1977).

According to Jehnsen & Melicher (1994) bankruptcy is the dangerous result for firms that face financial difficulties but not all distressed firms end up in business failure. They considered financial distress as a stage that can lead to bankruptcy. Accordingly, they measured firm's financial distress as a continuous state range from being financially weak to bankrupt.

Ward and Forster (1997) have suggested that loan default models are better in predicting financial distress than bankruptcy models. Likewise, Kahya & Theodossiou (1999) classified financially distressed companies based on a debt default criterion, such as defaulting on the payments on a company's debt, as well as when attempting to renegotiate these debts.

Similarly; financially distressed companies have been classified by Platt & Platt, (2002), based on their profitability, ability to pay dividend and being clients of consulting firm. They argued that most models used bankruptcy as a dependent variable because the timing of filing for bankruptcy is generally known. Using financial distress as the dependent variable is a better approach to failure prediction since the distressed company is a former stage to bankruptcy.

Many papers had classified firms as financially distressed based on negative operating income (John et al., 1992; Onur OZ, 2017; Shrivastava et al., 2018). In these papers, financial distress for active listed firms have been defined as having negative operating income before tax for two consecutive years.

Asquith et al. (1994) have examined 102 US firms and found that poor operating income is the main reason for financial distress. Based on these findings, they reported that interest coverage ratio (EBITDA/interest expenses) determines the health of the company. Having a negative ratio indicates that the firm is financially distressed, (Asquith et al., 1994; Andrade & Kaplan, 1998).

According to Platt & Platt (2008), classification of financially distressed firms must meet three criteria; negative operating income, negative operating income before interest and tax divided by interest expenses (Asquith, *et al*., 1994), and negative net income before special items (Hofer 1980).

On the other hand, Whitaker (1999) had found in his sample that all financially distressed firms presented a decline in their market value, therefore, he classified companies in financial distress when a reduction in their market capitalization resumed for 2 consecutive years.

Later, Pindado et al., (2008) completed the above findings and adopted a definition of financial distress that evaluated the ability of a company to satisfy its financial obligations. He argued that the firm would be unable to pay its debt obligations when its financial expenses exceeded its operating income before depreciation and amortization for two consecutive years. If this occurred and accompanied with a decline in the firm's market value for these years, thus, the company would be financially distressed. Afterward, several papers used the above-mentioned definition of financial distress, (Tinoco & Wilson, 2013; Rezende *et al.,* 2017).

The recent world financial crisis has increased the number of bankrupt companies in many countries, this resulted in developing a new area in the prediction literature to respond to the need of this phenomenon. The idea of generalizing a model for several regions in the world is pioneered by Platt & Platt (2008). They studied firms that face operating difficulties in three regions, namely, United States, Asia and Europe. Using logistic regression and data one year before operating difficulties incurred, the results indicate that a regional model performs better than a global model and the difference is related to macroeconomic factors and Labor conditions. Later on, few studies focused on predicting bankruptcy/distress globally or at least by region, i.e. (Onur Oz and Yelkenci, 2017; Alaminos *et al.,* 2018; Laitinen & Suvas, 2013; Hazak & Mannasoo, 2010).

To generalize the Z Score model, Altman *et al*. (2017) tested the performance of the original Z-Score Model in an international context, and how re-estimating it using different statistical methods, i.e., logistic regression and different variables affect the classification performance in a diversified data. He found that when adding country specific variables to the original Z-Score Model, the prediction accuracy improved for several countries. The results show that the uniform model developed (using data from 29 countries and the results validated in 34 countries) works reasonably well, in most countries, and the accuracy level of the models, tested by countries, range between 75% to 90%.

As can inform from the literatures, to predict financial distress it is crucial to identify the method by which companies should be recognized as financially distressed or non-financially distressed. Besides, the econometric model to be used must be specified for this purpose.

3. Methodology

3.1 The Research Data

3.1.1 Data Source

Firm specific data are extracted from the ORBIS database of Bureau Van Dijk. The common international format of balance sheet in ORBIS database provides a useful data for this analysis.

The researchers selected listing firms in MENA stock market. Meanwhile, financial and governmental firms are excluded.

As for Macroeconomic data, they are obtained from International Financial Statistics (IFS) and the variable PV (Political Stability and the Absence of Violence) is extracted from the International Country Risk Guide website.

3.1.2 Population and Sample Characteristics

The initial sample consisted of 1075 non-financial, non-governmental listed firms. All firms that have more than 4 years missing data and unknown market capitalization are removed from the sample. Furthermore, firms that do not have the optimal variable set of independent variables used eventually in the models are also excluded from the firm sample.

The panel data set covers a nine-year period from 2009 to 2017 annual data. All data are end-of-year figures and all nominated in terms of US million dollars.

The final sample consists of 796 listed MENA firms. The number of qualified observations by country is presented in Table 1. The first two columns refer to the countries in the sample, and the number of firms in each; the next two columns represent the total year observation of healthy (NFD) and financial distress (FD) observations for each country in the sample. When dividing the observations between the estimation sample and the holdout sample, total observations for each is presented in column 5 and 6 for the estimation sample, and in columns 7 and 8 for the holdout sample. The last column presents the total number of FD years for each country in the sample divided by the total number of observations in this country.

It can be informed from the last column that SA (Saudi Arabia) has the least number of financially distressed firms' years relative to its total years' observation, followed by QA (Qatar) and MT (Malta), while IQ (Iraq) has the highest number.

For the whole sample, the number of observations is enough to estimate and validate the results, (see Hair et al, 2014). Furthermore, Hair et al, (2014, p. 318) suggests that "the researcher should strongly consider dividing the sample into the analysis and holdout samples as a means of validating the logistic model".

According to Harrell et al, (1996) the number of observations kept for validation should be always less than half and usually it is 20–30 percent of the whole sample. In this study the number of the estimation observations is 5,535 (5057+478) and the number of observations reserved for validation is 1,506 (1312+194) and it represents 21% of the whole sample.

Table 1. The number of qualified observations by country

	Co.	# of observation in the whole sample		# of observation in estimated sample		# of observation in holdout sample		
Country		NFD Years	FD	NFD	FD Years	NFD Years	FD	FD/TOTAL
AE	39	334	17	262	11	72	6	0.048
BH	17	135	16	105	12	30	4	0.106
EG	129	1065	90	851	50	214	40	0.078
IQ	31	198	61	169	47	29	14	0.236
IR	142	1058	179	831	140	227	39	0.145

JO	79	602	99	488	64	114	35	0.141
KW	80	644	71	504	56	140	15	0.099
MA	46	387	19	311	10	76	9	0.047
MT	11	92	5	72	5	20	0	0.052
OM	64	522	40	416	31	106	9	0.071
PS	19	149	19	118	15	31	4	0.113
QA	21	181	8	141	6	40	2	0.042
SA	92	795	32	623	21	172	11	0.039
TN	26	207	16	166	10	41	6	0.072
Total	796	6369	672	5057	478	131	194	0.095

Where: AE= United Arab Emarat, BH= Bahrain, EG= Egypt, IQ= Iraq, IR= Iran, JO= Jordan, KW= Kuwait, MA= Morocco, MT= Malta, OM= Oman, PS= Palestine, QA= Qatar, SA= Saudi Arabia, and TN= Tunisia.

*NFD = Non-Financially Distress, and FD= Financially Distressed

Finally, Table 2 shows that the data include 6369 healthy firm-year observations, and 672 financially distressed firm-year observation. The percent of 9.54% is not different from the previous papers that used logistic regression as a statistical technique to estimate the probability of financial distress, i.e. Tinoco and Wilson (2013), had 5% distressed years in their sample that consist of 21,964 healthy firm-year observations and 1254 financially distressed firm-year observations; Ohlson (1980) had a sample of 105 bankrupt firms and 2058 non-bankrupts firms; and Platt and Platt (2008) had a sample of 4078 healthy firm-years and 590 financially distressed firm-years.

Table 2. Summary statistics for annual observation for distressed and non-distressed firms-years in the whole sample

NDF	FD	Total	% distressed
6369	672	7041	9.54%

3.2 Division of Sample

An important step in developing a prediction model is to provide a criterion to divide the firms in the sample between financially distressed and healthy ones. Recently, many authors have included in their sample active firms as well as bankrupt ones, (i.e. Gupta, 2018; Tinoco and Wilson2013; and Asquith, et al, 1994). Others measured financial distress on active companies using theoretical criteria to distinguish between poor financially health firms and financially healthy ones, (John, et al, 1992), (Platt and Platt 2002 and 2008), (Pindado *et al.,* 2008; Onur Oz, 2017).

The World Bank (2015) indicates that it takes on average 3.1 years for bankruptcy procedures in the MENA region countries to be completed. Besides, the different insolvency legislation in the MENA region' countries can alter the separation of the companies according to the legal definition.

Financial distress in this study is defined based on a combination of measures. First, following Pindado et al (2008), two main conditions must be met to perceive the financial distress in a given firm-year. The firm is classified as financially distressed whenever its financial expenses exceed its earnings before interest and taxes, depreciation and amortization (EBITD & A) for 2 consecutive years accompanied by a decline in its market value in these 2 years, (Pindado *et al.,* 2008).

Second, following John *et al.* (1992), when the firm has negative EBIT for 2 consecutive years, it is considered a firm in distress in the year that follows. Even though, negative EBIT does not apply that a firm will be bankrupt soon or eventually will fail, but it raises questions about the capability of the firms' operation (Platt & Platt, 2002).

3.3 The Research Variables

Based on literature review several variables are chosen due to their repetitiveness from previous studies. To select the independent variables, a univariate analysis was performed. First, the test for equality of mean values between the financially distressed and no-financially distressed observations is performed for each variable in the sample. Then, the variables that proved to be significantly different between distressed and non-distressed years were further tested using univariate logistic regression techniques. A model for each of these variables is performed. A univariate analysis is a common practice in the literature, Deakin, (1972) and Ohlson, (1980), for example, used this analysis.

Then, multicollinearity diagnostics tests are performed on the variables that prove to have the ability to predict financial distress when standing alone in the model to identify the set of variables that should not be included together in the final model. Finally, extensive investigations are performed using multivariate logistic regression to reach the final set independent variables presented in Table 3.

Table 3. The research variables

Dependent Variable	
Financial Distress	Binary variable denoted as 1 when the firm's year is financially distressed, and 0 otherwise.
Independent variables:	

Categories	Variables	Expected signs
Liquidity Ratios	WC/TA: Working Capital/Total Assets	-
Profitability Ratios	EBIT/TL: Earnings Before Interest and Tax/ Total Liabilities S/TA: Sales/ Total Assets	-
Leverage Ratios	RE/TA: Retained Earnings/ Total Assets	-
Cash Flow Ratios	CF/OR: Cash Flow/Operating Revenue OCF/TA: Cash Flows from Operations / Total Assets	- -
Macroeconomics Variables	PV: Political Stability and the Absence of Violence. CPI: Consumer Price Index	- +
Dummy Variables	Quantitative dummies take number 1 when country included 0 otherwise	

3.4 Statistical Model

To examine the research questions, a binary logistic regression is performed to examine whether the independent variable(s) can predict the dependent variable. The sample is divided into two groups, financially distressed firm-years and healthy firm-years. The categorical dependent variable is denoted as 1 when the firm-year is financially distressed, and 0 otherwise.

The binary logistic regression analysis does not require restrictive assumptions as linear regressions do. The major assumption is that the outcome variable must be dichotomous. There should be no multicollinearity among the independent variables, there should be no outliers, and there should be a linear relationship between the odds ratio and the independent variable (see Hair et al, 2014).

To clear the data from outliers, observations are winsorized (at the 99th % and the 1st %) and replaced with their winsorized values. To test for multicollinearity, correlation matrixes are performed (see later in the section 4). Finally, it is recommended a larger sample with the maximum likelihood method. These assumptions are well justified in the data set

Four models are performed to test the research hypotheses:

MODEL A (Firm Specific Variables)

$$logit\big(P(X)\big) = \beta_0 + \beta_1 * \frac{WC}{TA} + \beta_2 * \frac{EBIT}{TL} + \beta_3 * \frac{RE}{TA} + \beta_4 * \frac{S}{TA} + \beta_5 * \frac{CF}{OR} + \beta_6 * \frac{OCF}{TA}$$

Where

- WC/TA is working capital (current assets – current liabilities) divided by total assets.
- EBIT/TL is earnings before interest and tax divided by total liability
- RE/TA is retained earnings divided by total assets
- S/TA is sales divided by total assets
- CF/OR is operating cash flow divided by operating revenue
- OCF/TA is operating cash flow divided by total assets.

MODEL B (Firm Specific Variables with Size)

$$logit(P(X)) = \beta_0 + \beta_1 * \frac{WC}{TA} + \beta_2 * \frac{EBIT}{TL} + \beta_3 * \frac{RE}{TA} + \beta_4 * \frac{S}{TA} + \beta_5 * \frac{CF}{OR} + \beta_6 * \frac{OCF}{TA} + \beta_7 * lnmcap$$

Where:

WC/TA is working capital/total assets; EBIT/TL is earnings before interest and tax/total liability; RE/TA is retained earnings/total assets; S/TA is sales/ total assets; CF/OR is operating cash flow/operating revenue; OCF/TA is operating cash flow/total assets; LNMCAP is the natural logarithm of market capitalization (price per share for the company * number of shares outstanding).

MODEL C (Firm Specific Variables, Size and Countries Dummies)

$$logit(P(X)) = \beta_0 + \beta_1 * \frac{WC}{TA} + \beta_2 * \frac{EBIT}{TL} + \beta_3 * \frac{RE}{TA} + \beta_4 * \frac{S}{TA} + \beta_5 * \frac{CF}{OR} + \beta_6 * \frac{OCF}{TA}$$

$$+\beta_7 * lnmcap + \beta_8 * BH + \beta_9 * EG + \beta_{10} * IQ + \beta_{11} * IR + \beta_{12} * JO + \beta_{13} KW$$

$$+\beta_{14} * MA + \beta_{15} * MT + \beta_{16} * OM + \beta_{17} * PS + \beta_{18} * QA + \beta_{19} * SA + \beta_{20} * TN$$

MODEL D (Firm Specific Variables, Size, Countries Dummies and Macroeconomic Variables)

$$logit(P(X)) = \beta_0 + \beta_1 * \frac{WC}{TA} + \beta_2 * \frac{EBIT}{TL} + \beta_3 * \frac{RE}{TA} + \beta_4 * \frac{S}{TA} + \beta_5 * \frac{CF}{OR} + \beta_6 * \frac{OCF}{TA}$$

$$+\beta_7 * lnmcap + \beta_8 * BH + \beta_9 * EG + \beta_{10} * IQ + \beta_{11} * IR + \beta_{12} * JO$$

$$+\beta_{13} KW + \beta_{14} * MA + \beta_{15} * MT + \beta_{16} * OM + \beta_{17} * PS + \beta_{18} * QA$$

$$+\beta_{19} * SA + \beta_{20} * TN + \beta_{22} * PV + \beta_{23} * lncpi$$

- Where:
- WC/TA is working capital/total assets; EBIT/TL is earnings before interest and tax/total liability; RE/TA is retained earnings/total assets; S/TA is sales/ total assets; CF/OR is operating cash flow/operating revenue; OCF/TA is operating cash flow/total assets; LNMCAP is the natural logarithm of market capitalization (price per share for the company * number of shares outstanding).
- AE (United Arab Emarat), BH (Bahrain), EG (Egypt Republic), IQ (Iraq), IR (Iran), JO (Jordan), KW (Kuwait), MA (Morocco), MT (Malta), OM (Oman), PS (Palestine), QA

(Qatar), SA (Saudi Arabia), and TN (Tunisia)

- PV is political stability and absence of violence
- LNCPI is the natural logarithm of consumer price index

3.5 Research Hypotheses

H1: Firm specific variables (Model A) can predict financial distress for listed MENA companies

H2: Firm specific variables and size proxy (Model B) can predict financial distress for listed MENA companies better than financial ratio alone.

H3: Country dummies in (Model C) can enhance the prediction ability of (Model B)

H4: Macroeconomic variables in (Model D) can enhance the prediction ability of (Model C)

4. Empirical Results

4.1 Descriptive Statistics

Table 4 provides the descriptive statistics of the selected variables in the model. It consists of data from 2009 till 2017, and presents the mean, median, and standard deviation values.

In the table it is notable that the mean and median ratios are higher for non-distressed firms' years than both distressed firms' years and the whole sample years, except for CPI it is the highest in financially distressed firms' years.

The mean value of liquidity ratio WC/TA shows a higher portion of working capital to total assets in non-distressed firms' years. This indicates that in crisis times, the company manages to collect from its customers and pays short term obligations. On average, working capital for the whole sample is 14.90 percent of the total assets. In healthy firms-years the Mean and Median are larger than for financially distress, (mean and median are 0.164, 0.151 for healthy firms' years, and -0.002, 0.045 for financially distressed firm years respectively).

Table 4. Descriptive statistics of the selected independent variables for the whole sample (2009-2017)

	Healthy Years			Financially Distressed Years			All Years		
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
WC/TA	0.164	0.151	0.248	-0.001	0.045	0.424	0.149	0.140	0.274
EBIT/TL	0.295	0.161	0.649	-0.203	-0.047	0.830	0.248	0.142	0.684

RE/TA	0.083	0.089	0.301	-0.491	-0.205	0.993	0.028	0.080	0.452
CF/OR	0.174	0.156	0.203	-0.083	-0.083	0.282	0.149	0.139	0.225
OCF/TA	0.069	0.070	0.105	-0.015	-0.016	0.137	0.061	0.063	0.111
S/TA	0.725	0.604	0.631	0.528	0.480	0.510	0.707	0.583	0.623
LNMCAP	4.408	4.408	1.881	2.721	2.718	1.627	4.247	4.331	1.923
PV	0.685	0.676	0.095	0.629	0.652	0.094	0.679	0.674	0.096
LNCPI	4.806	4.701	0.309	4.898	4.775	0.315	4.815	4.709	0.311

The mean of the profitability ratio EBIT/TL has a negative sign in distress firm years, which indicates that these firms are not generating income in these years. Mean and median for healthy firm-years observations are 29.5%, 16.1% for EBIT/TL while these numbers are negative ones for financially distressed firm-years observations (-20.3% and -4.8%). Also, for RE/TA which is a measure of leverage since it can indicate whether the firm has the ability to finance its project from internal generated funds and a measure of cumulative profitability of the firms, as well as, according to (Altman, 1968), the age of the firm. This ratio has a mean of -4.91% and median of -2.06%, while it is a positive number of healthy firms' years.

As for the Sale to total asset ratio (S/TA), the mean and median values for financially distressed firms' years is lower than those of non-financially distressed ones. This ratio has a mean of 52.8% and median of 48%, for financially distressed years and mean of 72.5% and median of 69%, for non-financially distressed ones.

The mean value of the cash flow ratios CF/OR, and OCF/TA is positive for healthy firms' years, and negative for financially distressed firms' years. The medians are also positive for non-financially distressed firms' years, and negative for financially distressed ones and this indicates that cash disbursements are higher than the cash receipts from operation in financially distressed years.

The size effect on financial distress is measured by LNMCAP, the natural logarithm of market capitalization of the firm. This variable indicates a difference in means and medians between financially distressed firm's years and healthy ones. Healthy-years companies have a higher value on average (mean of 4.408 and median of 4.308 compared to mean 2.721 and median 2.718 for financially distressed firms).

PV is a measure of political stability and the absence of violence. The higher the number, the more stable the country is; therefore, it is hypothesized that PV is negatively correlated to financial distress since the more disturbed the country is, the more financially distressed the firms are. For financial distress firms' years, the PV value is less than those of non-financial distressed firms' years, PV has mean, and median values of 68.5%, and 67.6%

respectively for healthy firm's years and 62.9% mean, and a 65.2 % median for financially distressed ones.

Consumer Price Index (CPI) is used as a proxy measure of inflation. A rise in CPI indicates that inflation has raised, and the firm needs more funds to sustain its daily operations which may force firms to increase their debt. Therefore, it is hypothesized that a positive relationship exists between CPI and financial distress. LNCPI (the natural logarithm of CPI) has mean, and median values of 4.806 and 4.701 respectively, of healthy firms-years and 4.897 mean, and 4.775 median for financially distressed ones, with higher deviation for financially distressed years.

4.2 Correlation

To detect the relation between variables, correlation matrix is used. Table 5 shows correlations among variables included in the models: accounting ratios, the size proxy and macroeconomic variables.

Table 5. Correlations matrix among accounting ratios, the size measurement and macroeconomic variables

Probability	WC/TA	EBIT/TL	RE/TA	S/TA	CF/OR	OCF/TA	LNMCAP	PV	LNCPI
WC/TA	1.000								

EBIT/TL	0.236	1.000							
	***	-----							
RE/TA	0.360	0.286	1.000						
	***	***	-----						
S/TA	0.045	0.097	0.098	1.000					
	***	***	***	-----					
CF/OR	0.170	0.399	0.346	-0.142	1.000				
	***	***	***	***	-----				
OCF/TA	0.092	0.344	0.269	0.152	0.307	1.000			

	***	***	***	***	***	-----			
LNMCAP	-0.059	0.186	0.250	-0.044	0.329	0.262	1.000		
	***	***	***	***	***	***	-----		
PV	-0.006	0.021	0.088	-0.079	0.076	0.136	0.340	1.000	
	0.639	*	***	***	***	***	***	-----	
LNCPI	-0.067	0.013	0.005	0.151	-0.047	-0.138	-0.183	-0.276	1.000
	***			***	***	***	***	***	-----

***significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level

According to (Field 2009, p. 224), multicollinearity exists between independent variables when correlation is greater than 0.8. As evident in the table, no multicollinearity exists between the independent variables.

4.3 The Estimated Models

Models in this paper are derived using a panel data logistic regression. The model's coefficients are estimated by using firm specific variables and macroeconomic information from 2009 to 2015. The models were evaluated using 2016 and 2017 data.

Table 6 presents the 4 models developed in this study. The first model includes only firm specific variables as predictor variables (Model A). The second model includes size proxy in addition to firm specific variables as predictors to examine the size impact on the probability of financial distress (Model B). Following, country dummies are added to (Model B) to explore the effect of countries' differences in financial distress. Finally, macroeconomic variables PV, CPI, are added to (Model C) in (Model D)

Table 6. The models

	Model A	Model B	Model C	Model D
C	-1.777	-0.500	-0.311	12.290
	***	***	0.426	***
WC/TA	-0.661	-0.862	-0.516	-0.618
	***	***	**	***
EBIT/TL	-0.290	-0.215	-0.281	-0.287

	***	***	***	***
RE/TA	-1.165	-0.867	-1.178	-1.173
	***	***	***	***
S/TA	-0.420	-0.529	-0.790	-0.883
	***	***	***	***
CF/OR	-2.591	-2.367	-2.530	-2.692
	***	***	***	***
OCF/TA	-3.503	-3.025	-2.521	-2.892
	***	***	***	***
LNMCAP		-0.334	-0.373	-0.362
		***	***	***
PV				-24.089
				***
LNCPI				1.570
				***
Countries' Dummies	NO	NO	YES	YES

Where: WC/TA is working capital/total assets; EBIT/TL is earnings before interest and tax/total liability; RE/TA is retained earnings/total assets; S/TA is sales/total assets; CF/OR is operating cash flow/operating revenue; OCF/TA is operating cash flow/total assets; LNMCAP is natural logarithm of Market capitalization.

***significant at the 0.01 level; **significant at the 0.05 level; *significant at the 0.1 level

Test statistics for models				
LR statistic	741.16	838.69	946.324	1,150.321
PROB LR statistic	***	***	***	***
McFadden R^2	0.228	0.258	0.291	0.353
Akaike info criterion	0.457	0.440	0.425	0.389
Schwarz criterion			0.450	0.416
H-L Statistic	50.063	26.499	14.178	9.905
Prob. Chi-Sq8	0.000	0.001	0,077	0.272

Classification Accuracy				
Estimation Sample				
Specificity%	79.32	79.36	80.56	82.18
Sensitivity %	79.32	79.36	80.54	82.22
Total accuracy%	79.32	79.36	80.56	82.19
Holdout sample				
Specificity%	83.23	84.45	83.16	76.91
Sensitivity %	83.23	84.45	83.51	76.80
Total accuracy%	83.23	84.45	83.20	76.89
The whole sample				
Specificity%	80.78	80.84	81.68	81.22
Sensitivity %	80.80	80.95	81.70	81.25
Total accuracy%	80.78	80.85	81.68	81.22
Obs with Dep=0	5,057	5,057	5,057	5,057
Obs with Dep=1	478	478	478	478

The firm specific variables and macroeconomic factor coefficients are significant in all models and have the expected signs. Accordingly, the probability of financial distress is negatively related to all firm specific variables, size proxy, as well as to PV and positively related to CPI. These results are proven to have the expected signs as well.

Firms with low ratio of RE/TA, do not have the capacity to finance their project from internally generated funds which will make them rely on debt and pay interest. With the increase of debt, the cost of financing the debt will increase, and this in turn will increase the risk of defaulting in debt payment. The decrease in this ratio, which is also a measure of accumulated profitability, and implicitly it is an indicator of firm age. The less the accumulated profitably could mean that the company is newly established, (Altman, 1968), which indicates that the newly established firm may be more exposed to being in distress.

Unprofitable firms most likely will experience financial distress. These firms do not have enough funds to run their operations, pay their debt obligations, pay dividends to their stockholders, and expand their project except through dept.

Liquidity ratio and cash flow ratios give signs about the working capital management's efficiency, especially in periods of crisis. Higher liquidity and cash flow from operations show that the firm can collect cash from customers and pay short term creditors. The negative sign of the coefficients of liquidity ratio and cash flow ratios indicate that firms with lower liquid assets are most likely to be in financial distress; therefore, the need for effective working capital management is vital for firms, especially in emerging countries, as MENA countries, where the frailer of payment for goods and services is widespread (Zikovic, 2017).

Size is another statistically significant firm specific variable in explaining financial distress. The negative sign indicates that small firms have more tendency to be in financial distress. These firms are usually less known than large firms and this could limit their access to financing especially in periods of financial crisis.

To test the country of origin (where firms operate) effect on the probability of distress, country dummies are added (AE reference dummy). The results indicated that only 3 countries are significantly different from AE (United Arab Emirates), BH, IQ and IR (Bahrain, Iraq and Iran) in Model C and all countries except MT (Malta) and QA (Qatar) are significantly different from AE.

The Likelihood Ratio test is performed for all Models. The results show statistically significant improvement in models B, C, and D relative to model A which indicate that the addition of size and country dummies and macroeconomic variables have enhanced Model A.

McFadden R^2 Statistics show improvement in the models which include countries dummies and macroeconomic variables over the models that include only firm-specific variables (accounting ratios and firm size).

Akaike info criterion indicates improvement in models over model A. The best model according to this criterion is the one with the lowest value.

Results obtained with Hosmer–Lemeshow Test indicate that the null hypothesis of the model fits are accepted for models, C and D, only.

The models exhibit accuracy range from 79 % to 82 % for estimation data and 75% to 84% for holdout data. In addition, models without country effects have slightly better out-of-sample predictive accuracy, when macroeconomic variables are added, the out of sample accuracy declined.

4.4 Evaluating the Models Across Countries

The analyses will be further justified by cross country validation of the models. The cutoff values of Model C, and Model D are calculated for the whole sample, and the estimated coefficient of the models is applied to the whole sample to prepare the classification accuracy tables for each country.

For Model C, the cut off point for the whole sample is 0.097 and the prediction accuracy is 81.68%

Table 7 presents the classification accuracy by countries for model C. Total accuracy prediction for the countries range from 56.10% to 95.32%, the lowest performance of the model exhibited by IR and the highest by QA. Except for IR the total accuracy classifications of the prediction model ranges from good to excellent.

Table 7. Accuracy classification table by countries for model C

Country	Specificity	Sensitivity	Total accuracy
United Arab Emarat (AE)	94.01%	52.94%	92.02%
Bahrain (BH)	76.30%	93.75%	78.15%
Egypt Republic (EG)	91.64%	74.44%	90.30%
Iraq (IQ)	67.68%	90.16%	72.97%
Iran (IR)	51.13%	85.47%	56.10%
Jordan (JO)	76.41%	86.87%	77.89%
Kuwait (KW)	78.57%	80.28%	78.74%
Morocco (MA)	96.64%	68.42%	95.32%
Malta (MT)	88.04%	80.00%	87.63%
Oman (OM)	90.23%	82.50%	89.68%
Palestine (PS)	79.87%	94.74%	81.55%
Qatar (QA)	96.61%	83.33%	95.77%
Saudi Arabia (SA)	95.05%	83.33%	94.20%
Tunisia (TN)	92.27%	68.75%	90.58%

Model D has a cutoff value for the whole sample is 0.094 and the prediction ability of the model is 81.22%

Table 8 presents total accuracy table by countries for Model D. Total accuracy prediction for the countries ranges from 70.17% to 94.83%, the lowest performance of the model exhibited by IR as well, and the highest by MA. The model performed well in most countries and total accuracy classifications of the prediction model ranges from good to excellent (70.17% to 94.83%).

Table 8. Accuracy classification table by countries for model D

Country	Specificity	Sensitivity	Total accuracy
United Arab Emarat (AE)	83.53%	70.59%	82.91%
Bahrain (BH)	72.59%	100.00%	75.50%
Egypt Republic (EG)	89.77%	73.33%	88.48%
Iraq (IQ)	66.16%	86.89%	71.04%
Iran (IR)	68.90%	77.65%	70.17%
Jordan (JO)	70.60%	88.89%	73.18%
Kuwait (KW)	72.36%	85.92%	73.71%
Morocco (MA)	96.12%	68.42%	94.83%
Malta (MT)	84.78%	60.00%	83.51%
Oman (OM)	89.27%	82.50%	88.79%
Palestine (PS)	84.56%	89.47%	85.12%
Qatar (QA)	94.22%	87.50%	93.65%
Saudi Arabia (SA)	86.06%	96.00%	87.56%
Tunisia (TN)	86.47%	75.00%	85.65%

The results obtained for validating the model across countries match Altman et al, (2017) accuracy rate, (75% to 90%) and outperform Laitinen and Suvas, (2013) accuracy rate, (54.6% to 83.7%).

By testing the equality of means for the accuracy results from Model C and Model D the results indicated that the predictive accuracy for Model C is not significantly different from Model D. Therefore, based on this and on the test statistic for the models, macroeconomic variables add value to the prediction model and alternative hypothesis 4 is accepted.

As a conclusion for the above, all models can predict financial distress for listed companies in the MENA region. However, adding size proxy, country effects and macroeconomic variables to the model enhance the model goodness of fit measurement compared to the Model A. Model D statistical measurements are the best among all. These findings provide evidence that financial accounting ratios, firm size, country dummies, and macroeconomic variables PV and CPI should be included when predicting the probability of distress.

5. Conclusion

The primary objective of this study is to develop a model that can predict financial distress specially designed for MENA listed firms. To develop the model a set of firm specific variables, size proxy and macroeconomics variables were examined to determine their usefulness in predicting financial distress for listed MENA firms.

The World Bank (2015) indicates that it takes on average 3.1 years for bankruptcy procedures in the MENA region countries to be completed. Besides, the different insolvency legislation in the MENA region, countries, can alter the separation of the companies according to the legal definition. Furthermore, the complications in implementing bankruptcy legislation in emerging economies, (Zikovic, 2017), and the unavailability of data, using active firms can be helpful.

Therefore, financial distress in the paper is defined based on 2 criteria: i) Whenever financial expenses exceed operating income before depreciation and amortization for 2 consecutive years, accompanied by a decline in market value in these years, when this is true, the year that follows is considered a financially distressed year, and, ii) if the firm has negative operating income before Tax for 2 consecutive years, by this, the year that follows is considered a financially distressed year.

Several models were developed, using panel data, obtained from ORBIS database, International Financial Statistics (IFS), and the International Country Risk Guide website.

The first model included firm specific variables, the second included size proxy besides firm specific variables, and the third model test the effect of countries on the model that includes firm specific variables and size, finally, macroeconomics variables are added.

Four logistic regression models were developed, of which two were without country effects and the others included countries dummies. The significance of firm-specific variables and size, alongside with country effect and macroeconomic factors were examined.

The results indicate that firms in financial distress suffer from a working capital deficit, low or negative profitability, low or negative operating cash flow, and low or negative retained earnings. Besides, small firms also have a higher probability of distress, and when inflation raises and the political stability in the country declines the firms became more exposed to being in distress.

The data were divided into estimation sample and holdout sample. Models without country dummies performed better in the hold- out sample.

When validating the models, with the best fit measurement across countries, the results indicated that there isn't a significant difference between the Models that contain macroeconomic variables than that of the model that include company specific variables and countries dummies; however, the model fit measurement and the estimated coefficients improved. The results obtained from cross country validation of the model exhibit a good to excellent accuracy rate.

The research on prediction model is extensive and in the developing countries, it is still new. Further research on the subject should include other than listed firms, for example, small and medium enterprises.

The results in this study indicate that a uniform model of financial distress prediction can be developed, however, other variables should be tested, such as economic and monetary policy, and corporate governance measures

This study answer questions regarding country effects on financial distress prediction. Other effects such as industry effects should also be considered in future studies.

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