HAIGAZIAN UNIVERSITY

PREDICTING NON-PERFORMING LOANS THROUGH FINANCIAL RATIOS OF SMALL AND MEDIUM ENTITIES IN LEBANON

BY

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DEDICATION

I dedicate my dissertation work to my very supportive mother, to my amazing father, and everyone who believed in me.

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ABSTRACT

Of the Thesis of Marybel Richard Nasr for Master of Business Administration

Title: Predicting Non-Performing Loans through Financial Ratios of Small and Medium Entities in Lebanon

The purpose of the study is to examine the ability of financial ratios in the prediction of the financial state of the Small and Medium Entity in Lebanon. Specifically, the financial state of the company is determined by the classification of the loans of the SME, which can be performing or non-performing.

An empirical study was performed using a data analysis conducted on the financial statements of 222 SMEs in Lebanon for the years 2011 and 2012, of which 187 are subject to performing loan and 35 are subject to non- performing loans.

The Altman Z-scores were calculated, the independent sample t-test was performed, and models were developed using the logistic regression.

Empirical evidence from this study showed first, that the Altman Z-scores were able to predict the solvent state of SMEs having performing loans, but were unable to predict the bankrupt state of the SMEs having non-performing loans. Second, the independent sample t-test revealed five financial ratios that are significantly different between SMEs having performing loans and non-performing loans during the years under study, which are the following: liquid assets/current assets, total liabilities/total assets, total equity/total assets (disregarded subsequently, for being complimentary to the previous ratio), sales/total

liabilities, and working capital/total assets. Third, a logistic regression model was developed for each year under study and accuracy results were deducted and displayed in a table showing the percentage of accurately classified companies (solvent and bankrupt), in addition to the type I and type II errors.

This study recommended not applying the Altman Z-score models on SMEs in Lebanon due to the low accuracy results registered. Moreover, some financial ratios with predictive ability are worth focusing on during the analysis of the financial health of a company, which are liabilities/assets, liquid assets/current assets, sales/liabilities and working capital/assets.

Finally, since the logistic regression models developed in this study using only quantitative variables and a sample of 222 SMEs did not result in high accuracy levels, further research conducted on a larger sample using qualitative variables such as years of experience of the SME in the market, geographical location, history of repayment in the bank, overall macro-economic indicators… could add to the predictive ability of the logistic regression model in Lebanon.

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LIST OF ACRONYMS

Ast	**Assets**
Aver	**Average**
BDL	**Banque Du Liban**
BV	**Book Value**
Cur	**Current**
EBIT	**Earnings Before Interests and Taxes**
Eq	**Equity**
Exp	**Exponential**
Fix	**Fixed**
Inc	**Income**
Liab	**Liabilities**
Liq	**Liquid**
Log	**Logarithm**
Receiv	**Receivables**
SME	**Small and Medium Entities**
Tot	**Total**
Work Cap	**Working Capital**

CHAPTER ONE

INTRODUCTION

The banking sector, the backbone of every economy, faces many risks among which we can mention: market risk, operational risk, credit risk, liquidity risk… Each risk should be avoided if possible, or if that is not the case, its negative effects should be minimized.

Credit risk is the risk that the bank is unable to collect the clients' loan repayments on the predetermined time. Credit risk is directly related to the bankruptcy risk of the companies which constitute the bank's borrowers. The definitions of bankruptcy vary between the legal sense and the financial sense: some studies define bankruptcy as the act of filing for bankruptcy (for instance, filing for Chapter 11 bankruptcy in the US), while other studies use the bankruptcy definition of business failure being linked to default on a loan, and overdrawn bank account, or non-payment of preferred stock dividend.

The ability to accurately predict if a company will go bankrupt is not only important to every bank, but also to potential investors, existing shareholders, suppliers, clients and even the employees dealing with the subject company.

In this study, we aim to evaluate the ability of financial ratios to predict failure or solvency of a given firm. Thus, we will use the financial definition of bankruptcy, the criterion being the incapability of companies to fulfill their part in a financial banking transaction, in other words, their incapacity to repay in time the borrowed amounts within the conditions established in the loan agreement.

In Lebanon, the mentioned financial definition of bankruptcy could be applied through the Central Bank's differentiation of the performing and non-performing loans in the BDL Basic Circular No. 58, where the differentiation of the two categories is based on characteristics such as the repayment of a loan, account movement at the bank, financial state of the borrower, legal state of the borrower, the situation of the client with other banks… the criterion that is the most relevant is the repayment of a loan: borrowers having performing loans repay their dues on time or with delays not exceeding 90 days, whereas borrowers having non-performing loans are classified when the delays in repayment exceed 90 days

This thesis will focus on bankruptcy prediction of Small and Medium Entities in Lebanon through financials ratios, in other words the thesis will test if the financial ratios of a company can accurately predict if a SME is in the performing loans or non-performing loans category. The Central bank's definition of the Small and Medium Entities portfolio is included under BDL Basic Circular No. 115 as follows: a- loans granted to liberal professions such as doctors, engineers and lawyers in order to finance their professional activities, b- loans granted to sole proprietorships or to corporations (general partnerships, limited partnerships, jointly-owned companies, joint-stock companies including holdings, partnerships limited by shares, limited liability companies or offshore companies) the annual turnover of which does not exceed the equivalent of USD 5 million.

Three procedures will be used in this context: 1) application of bankruptcy prediction models on the financial statements of the SMEs subject to performing loans and SMEs subject to non-performing loans, 2) performance of the independent sample t-tests for the financial ratios of these SMEs and 3) estimation of models that can be applicable on the sample SMEs, using the binary logistic regression.

The bankruptcy prediction models or scoring methods were significantly developed with the use of statistical methods for analyzing the financial situation, starting from ratios. The bankruptcy prediction models which are selected from the literature review and will be applied in the study are: the Altman Z'-score and Altman Z"-score. These models were chosen among several models because they are technically applicable on the Lebanese financial statements, and because the Altman Z-scores are the most widely tested. As such, Altman's original Z-score model which was created in 1968, and was meant to be applied on manufacturing companies with a capital of over $ 1 million, contains the ratio "Market value equity/Book value of total debt", and since in Lebanon there is no stock exchange market for private companies, then the formula was not selected in this study. Altman's Z'-score and Z"-score were later derived from the original Z-score, each one with an attuned formula to a specific type of companies. The Z'-score is meant to be applied on privately-held manufacturing firms and the Z"-score is for both public and private non-manufacturing firms.

The second procedure consists of performing the independent sample t-test on 22 financial ratios selected from the literature review, which will indicate if there is a significant difference between the ratios of SMEs subject to performing loans and SMEs subject to non-performing loans.

The third procedure consists of estimating models based on the sample under study using the Logistic Regression. The regression model is constituted of independent variables and their related coefficients, which indicate the change each variable causes in the odds of the tested event happening or not. The dependent variable is in terms of odds ratio. The variables selected to be the independent variables are the financial ratios that prove to be the most predictive of bankruptcy, in other words, the financial ratios that jointly are the most significantly different for solvent SMEs compared to insolvent SMEs. The coefficients are generated from the system used (SPSS). The dependent variable is related to the classification of a given company as being subject to a performing loan or non-performing loan.

Being a credit risk analyst in a Lebanese bank, my job is to evaluate the risk of granting potential borrowers the requested facility and to monitor the status of existing borrowers. Thus, I chose this topic to go deeper into this field to evaluate the application of international prediction models in the Lebanese business market and the ability of financial ratios to predict the financial health of a company. In addition, predicting bankruptcy through financial ratios is a very interesting topic, which, according to my literature research, has not been studied extensively in Lebanon.

The purpose of this study is to identify which model is proven to be the most accurate in predicting default of SMEs in Lebanon. As such, if one or more models achieve high levels of prediction accuracy, the model(s) can be used by the Lebanese banks to make better credit granting decisions for new clients, or to better monitor the financial situation of existing borrowers. The results can also be used as a warning sign to the businesses on the verge of bankruptcy, enabling the owners to adopt corrective measures and avoid failure.

LCHAPTER 2

LITERATURE REVIEW

In the literature review that follows, the definitions of bankrupt firms, the analysis approaches used, being the Altman models, the financial ratios analysis and the development of customized models are presented.

2.1 Literature review

The first part of the literature review will present the papers which applied the Altman Z-score models, and the related results concluded.

Research shows that bankruptcy risk can be analyzed through several procedures, one of them being the analysis of bankruptcy risk through the score method. This method assesses risk through 3 features: a) forecasting the financial situation based on historical performance of the company; b) predicting the financial situation through several collective rates which indicate if a company is facing difficulties; c) conducting a comparative test between the records gathered about the state of companies with and without financial problems.

To apply the z-score method, a set of companies formed of two distinct groups must be under-study: a group of companies facing financial difficulties and a group of companies free of financial problems. A set of ratios is established for each group, and the best linear combination of ratios is determined: the goal is to combine the ratios in the best way that differentiates between the two groups of companies. The discriminant analysis is then applied and the Z score is obtained for each firm. The differentiation between solvent and insolvent companies is determined by the distribution of different scores (Bordeianu, Radu, Paraschivescu & Willipavaloaia, 2011).

Some researchers in Romania tested the Altman model along with three other bankruptcy prediction models (Taffler model, Anghel model, and Conan-Holder model) on the financials of one company for the years 2008, 2009, and 2010. The results of the different models for each year were compatible. All the models predicted that the company is unlikely to experience bankruptcy during all the years understudy. In addition, all models showed the lowest score in 2010 (Bordeianu, Radu, Paraschivescu & Willipavaloaia, 2011).

In his paper, Strobel aims to analyze and evaluate the methods used to measure the systematic soundness of the banking sector. The methods examined are 3 applications of z score: aggregate of individual balance sheets, median and mean (weighted), using a dataset of commercial, cooperative and savings banks for the Organization for Economic Cooperation and Development (OECD) countries covering the period 1994 to 2008. After refinement of the data, the remaining sample included data for 11,300 banks with an average of 10.7 years of observations. Calculations of descriptive statistics for these different aggregate Z–score measures (aggregate date, mean, median, weighted mean, weighted median, first percentile, and weighted first percentile) were made, such as mean, standard deviation, minimum, maximum. In addition, the respective Spearman’s rank correlation coefficients were calculated to give an indication of how consistently they perform as a measure of systemic soundness for the countries considered. The results show that: 1) the aggregated data-based measure gives results that are more similar to the ones obtained for the weighted mean/median -based measures than for the unweighted ones; but none of these correlations are close to being perfect, suggesting that the measures' implied rankings differ to some extent, 2) mean and median-based measures showed high correlations in their weighted and unweighted forms ; they are thus very similar in terms of how they assess countries' relative systemic soundness 3) weighted and unweighted measures have slightly different implications regarding the ranking of countries' systemic soundness 4) the median and first percentile-based measures have very different consequences for the relative ranking of countries' systemic soundness, making them a potentially useful addition to the aggregate insolvency risk measures reflecting systemic soundness (Strobel 2011).

- Another study's aim is to identify the predictive ability of both Altman and Kida models in giving an early sign of company bankruptcy, and also to find out which of the two models is more appropriate in predicting bankruptcy of a sample of Jordanian listed companies for the period between 1990 to 2006 for each year of the five years prior to liquidation.

Results show that companies that have a Z-score of > 0.38 are considered as a good sign for being successful compared to those which have a Z-score of < 0.38 had potential serious problems and may not be able to continue. The sample tested consists of companies listed on the Jordanian Stock Exchange that were liquidated during the period of 1990 - 2006. Only companies from services and industrial sectors were eligible for the study. Banking and insurance sectors were excluded from the study because they apply different financial ratios.

The final sample consists of 32 companies eligible for the study, 16 bankrupt companies and 16 successful companies. Financial ratios data were extracted from the annual reports of Jordanian public shareholding companies that were liquidated for the period 1990-2006 and the annual reports of the successful firms were also obtained from the Ministry of Trade and Industry.

The following three hypotheses were tested:

- Hypotheses 1: Altman model is unable to predict bankruptcy of companies during the 5 years prior to liquidation.
- Hypotheses 2: Kida model is unable to predict bankruptcy of companies during the 5 years prior to liquidation.
- Hypotheses 3: There are no statistically significant differences between the Altman and Kida Models for predicting corporate bankruptcy during the 5 years prior to liquidation.

Altman's model was able to predict companies' bankruptcy in the fifth year prior to the bankruptcy by 75%, while Kida's model was able to predict bankruptcy by 69% for the same year. The results of the fourth year that preceded the bankruptcy, an improvement is noted in the predictive ability of Altman's model where the rate reached 94%, compared to predictive ability of Kida's model having remained at the rate of 69%. These results support the rejection of the first and second hypothesis. The ability to predict bankruptcy improved to 100% in the Altman model while it remained the same at 69% for Kida model during the first 4 years prior to bankruptcy, then improved to 75% during the first year prior to bankruptcy.

Finally, although percentage rates and prediction frequencies for Altman Z-Score are better than those of Kida's Z-Score (Altman's model was comparatively the better model in bankruptcy prediction of Jordanian listed companies, where the average bankruptcy prediction rate in the past five years was 93.8%, compared to that of Kida's model where the average bankruptcy prediction rate in the past five years was 70.2%), the results support the acceptance of the third hypothesis that states that there are no statistically significant differences between the Altman and Kida Models for predicting companies' bankruptcy during the five years prior to liquidation (Alkhatib and Al Bzour, 2011) .

An article published in NYU Stern talks about Altman’s formula and its current applicability. Given the increasing demand for real-time information to manage risk, Edward Altman, 45 years after creating the Z score formula, launched a new application called “Altman Z-Score Plus,” in partnership with Business Compass LLC. The App is available for the iPhone, iPad, Android and BlackBerry mobile devices and desktops.

While the original Altman Z-Score covered the publicly traded US-based manufacturing companies, the new Altman Z-score Plus application also covers the non-US companies (including those in emerging markets) and non-manufacturing firms, both public and private (Z’’-Score), in addition to privately-held industrial manufacturing firms (Z’-Score). Some of the enhancements in the application are the assignment of a 1-to 10-year probability of default using rating classes from AAA to D (default), indicating the likelihood of bankruptcy for each company according to Z, Z' or Z”-Score. As for the Altman’s predictions for 2012, he forecasts an increase in the default rate of the U.S., and Europe's, high-yield corporate bond to possibly 4.0%, based on the two factors that have affected current yield spreads and distressed ratios: additional slowing of the U.S. GDP and a default in at least one European country's bonds (NYU Stern 2012).

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The following study by Li examines the prediction of corporate failures in the U.S. during 2008-2011. Three prediction models are examined: Altman's original Z-Score model, a re-estimated Z-Score model and a re-estimated model with an added variable. Many studies proved that Altman's Z – Score is effective in predicting corporate financial distress (e.g., more recently, Li & Rahgozar (2012), Satish & Janakiram (2011), Al Zaabi (2011), Gutzeit & Yozzo (2011), Wang & Campbell (2010), Lugovskaya (2010), Gerantonis, et. Al (2009), Xu & Zhang (2009)), however the Z score has its limitations. First, it uses unadjusted accounting data, data from relatively small firms, and old data. There is evidence that the Z-Score coefficients should be re-estimated for the prediction of corporate distress involving different time periods or different industries (Grice & Ingram 2001). Second, four of the ratios used are accounting-based, which is not forward looking because of the historical data used. Also, financial statements are prepared with a going concern assumption, in other words, companies are assumed not to file bankruptcy (Gharghori et al. (2006) and Hillegeist et al. (2004)). Third, the only ratio in Altman's original model is market-based and "forward looking" is (Market Value of Equity / Total Liabilities). (Gutzeit & Yozzo 2011). Furthermore, it doesn't include a measure of asset volatility, which is important because it measures the probabilities that the value of a firm's assets decline to an extent that it is unable to pay its debts (Hillegeist et al. (2004)). Also, the Z score provides a more accurate prediction for U.S. companies in certain periods than others. (Begley et al. (1996), and is better with manufacturing companies than with companies in other industries (Grice and Ingram (2001)). In fact, Gharghori et al. (2006) found the option-based models outperform the accounting ratio models after evaluating the performance of several default–risk models. Similarly, Black-Scholes-Merton option-pricing model is found to be superior to accounting-based measures in bankruptcy prediction (Hillegeist et al. 2004). Thus, a hybrid approach was created, which combines a market-based model and an accounting-based model (e.g. Altman's), and provides better bankruptcy prediction than either model alone. A market-based model is found to be significant in predicting default of companies with high credit risk, while the accounting-based model is significant in default prediction of those with low credit risk. Therefore based on a company's credit risk, the prediction accuracy can be improved by placing more emphasis on the market-based model while reducing the emphasis on the accounting-based.

- The sample in this research consists of all publicly traded companies that filed for Chapter 11 and Chapter 7 bankruptcies in the U.S. between 2008 and first quarter of 2011. Those companies were identified from two sources: COMPUSTAT and BankruptcyData.com. There were 106 companies and 66 companies that filed for Chapter 11 and Chapter 7 bankruptcies; respectively. Data were extracted for all 172 companies from COMPUSTAT and firms with incomplete or missing data were eliminated. The final sample size is 70. A matched pair process is used in the study. For each bankrupt firm, a solvent firm in the same industry and of the closest asset size in the bankruptcy year was identified. In conclusion, this study examined the accuracy of various Z-Score models in predicting corporate bankruptcy from 2008 through 2011. Although the original Z-Score model was developed for manufacturing firms, it performs equally well in predicting bankruptcy for non-manufacturing companies. The model with only one variable "Market value of equity/Total liabilities" appears to have the highest bankruptcy predicting power. Although it was a widespread criticism on Z-Score model, total asset variability did not appear to be a significant factor for bankruptcy prediction. On the other hand, there's evidence that asset volatility is a significant factor for the bankruptcy prediction of manufacturing firms (Li & Rahgozar 2011). In this study, the change in total assets from one year to two years prior to bankruptcy was considered as a substitute for asset volatility. Future research could focus on this area by using other proxies for asset volatility. In addition, all models tend to have high type II error of inaccurately predicting a solvent firm as bankrupt, so there is a need for developing a bankruptcy prediction model for the solvent firms (Li, 2012).

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The Z score is one of the few formulae that have not changed since its initiation (45 years ago) till now. In 2011, Altman, with the help of a tech-savvy former student, recently launched the Z-Score+ in an updated format as a smart phone application compatible with the biggest brands (iPhone/iPad, Blackberry, Android). In its online publication, The Street analyzed several solar energy product manufacturers after a bankruptcy filing in the sector which was not a first. As reported in NACM's eNews in January, Michigan-based Energy Conversion Devices (ECD) filed a petition for Chapter 11 protection. In fact, the solar products industry witnessed several high-profile bankruptcy filings, including Stirling Energy, as companies face high international competition, domestic market saturation and a lack of expenditure in the energy efficiency sector because of general economic and employment uncertainty. After applying the Z-Score, The Street declared that ECD's Z-Score was in the distress zone (1.49) and that several others in the industry were much more distressed and at high risk with scores of as -7.3 and -16.5. In this regard, Altman told

NACM that the timing of ECD's slip into bankruptcy seemed surprising given where it rated in the Z-Score compared to some others in the industry. Accordingly, this case is part of the reasons why Altman suggests the use the updated Z-Score+ version, because it takes more factors into consideration than the 1968 version or its mid-1990s update. The latest version contains some measures not found in the older versions. The Altman Z-Score+ was introduced in the form of a Smart-Phone/iPhone application and can also be downloaded to a laptop or home computer. It includes new predictors of the one-to-10-year likelihood of default and a bond rating equivalent rate to match the score. Regarding the bond rating equivalence, Altman noted that the previously mentioned ECD 1.49 Z-Score would likely translate into a "B-"to "CCC+" bond rating range. The score of "D" rating area, indicates a high likelihood of default. The release of the application is not the first time the Z-Score went beyond the scope of measuring domestic and/or manufacturing-based companies. The 90's update (the Z-Double-Prime) included such metrics, but did not appear to be applied as widely (and correctly) as the original '68 version. It also included considerations for non-manufacturers, mainly in retail as well as for international situations. However, Altman said that incorrect use of the Z-Score has been an ongoing occurrence and he hopes it ends with the introduction of the Z-Score+ app. Moreover, Altman found that a lot of people have been also using the Z-score formula incorrectly; they were using the classic Z-Score with scores based on the three zones (safe, grey, distressed), but they were using it based on zones established in the 1960s, and they were using it for non-manufacturers as well as manufacturing companies in the same way. But then the classic Z-Score only provides a score and general guidelines (trending up, trending down, zone, etc.). Strictly using the model developed almost a half-century ago instead of the newer models needs to be done with a good understanding of context and the activity of the company being measured (Shappell, 2012).

The primary objective of the authors Li and Rahgozar in their study is to re-examine the accuracy of the original Z -score in predicting corporate failures in the U.S. from 2000-2010. Furthermore, since a study by Hillegeist et al (2004) has indicated that Altman's model is deficient and fails to include a measure of asset volatility (which measures the probabilities that the value of a firm's assets decline to an extent that it is unable to pay its debts), the paper also addresses this deficiency; thus it explores whether asset volatility validates with Z - score in predicting bankruptcies.

- Altman's original model predicts that firms with Z-scores above 3 are unlikely to file for bankruptcy, and firms with Z - scores below 1.81 are likely to fail. Z- scores between 3 and 1.81 are considered "grey" area.
- The sample tested consists of all publicly traded companies that filed for Chapter 11 and Chapter 7 bankruptcies in the U.S. between 2000 and 2010. Data was obtained from two sources: COMPUSTAT and BankruptcyData.com (total 412 companies, after calculation of Z score and refinement of firms with incomplete or missing z scores, 252 firms). Then, one, two and averages of three and five years Z-scores prior to each firm filing for bankruptcy were calculated. The analysis of these Z-scores identifies which one is a superior predictor of financial failure. Since the original Z-score model was developed to predict bankruptcy of the publicly held manufacturing companies, and to re-examine whether Z-score predictions differ among different industries, the sample was divided into manufacturing and non-manufacturing companies. For each group, the average Z-score was calculated and compared

the prediction outcomes. Also, a coefficient of variations for all firms that the Z -score accurately predicted their failures was calculated, to address asset volatility and corporate bankruptcy. It is assumed that if asset volatility is a missing variable from the Altman's model, the volatility measured by a coefficient of variations and Z -score bankruptcy predictions somehow has to be correlated (firms with high coefficients of variations to have a Z-score closer to bankruptcy level). Total asset volatility is a more important variable when using the Z-score model to predict bankruptcy for manufacturing firms than for non-manufacturing firms. The results reveal that out of 252 firms, the number and percentage of accurate bankruptcy predictions applying one and two-year z -scores are 156 (61.90%) and 171 (67.86%) respectively, while accurate prediction by averages of three and five -year are 178 (70.63%) and 194 (76.98%). These estimates imply that observations of financial performances over a longer period (i.e., 5 -year) could lead to better predictions of financial distress than a shorter period like one or two years. For the 33 firms filing for Chapter 7, the average five-year Z -score provides the highest accuracy prediction rate (76%) and the lowest inaccurate predication rate (15%); and these findings are consistent with the firms that filed for Chapter 11 bankruptcies. The results also revealed that the Z-score predictions for non-manufacturing firms are as valid as those for manufacturing firms where the average three and five-year Z -scores provide approximately equal accurate bankruptcy prediction rates for manufacturing and non-manufacturing firms (70.33%, 70.81% and 75.82, 77.64%). Finally, the correlation between percentages of accurate bankruptcy predictions for manufacturing firms using average three-year Z -score and total asset risk is 0.08 (asset volatility coefficient) for manufacturing firms, while the correlation using average five-year Z -score is 0.75. For non -manufacturing firms, the correlations figures are 0.30 and 0.11, respectively.

These results imply that total asset volatility might be a missing variable when using the average five -year Z -score and the original model to predict bankruptcy for manufacturing firms. However, for non -manufacturing firms, three -year average Z-score and total asset risks have higher correlations (Li and Rahgozar, 2012).

The accuracy of the Z' score in prediction of bankruptcy in New Zealand was studied in 2012 through a research note. Some limitations of failure prediction models were identified, such as the failure to emphasize the importance of non-financial factors and the effect that these may have had on the business's failure. Examples include management, personnel, products and equipment. Another limitation is the fact that a single model is not suitable for predicting business failures across different types of firms and different industries. In addition, accuracy levels of failure prediction models are dependent on the model used and the period of time prior to failure. As for the methodology of the paper, the authors chose 20 companies from the list of the 45 finance companies which collapsed between May 2006 and July 2011. Their annual reports were downloaded from the New Zealand Companies Office website, and the individual components of the Z'-score model were entered into an Excel spreadsheet. The results showed that of the 20 companies: one company showed a z-score in the "tend not to fail" area five years to bankruptcy, while its z-scores for the years 4,3,2, and 1 to bankruptcy all showed z scores in the "tend to fail" area. Another company had a z score of in the "grey" area in the year it went bankrupt, while its z-scores in the years 5,4,3, and 2 from bankruptcy all showed z scores in the "tend to fail" area. A third company had a z score in the "grey" area one year prior to bankruptcy, while the year of bankruptcy in addition to years 5,4,3, and 2 from bankruptcy all showed z scores in the “tend to fail” area. The remaining 17 companies all had z-scores in the “tend to fail” area during the years under study. With the exception of one company with a score of 4.88 five years prior to failure, Altman’s (2000) Z’-score criteria suggests all the companies in the sample were likely to collapse (Samkin, Low and Adams, 2012).

Failure prediction was also tested through a case study in Jordan. More specifically, the authors aimed to test the generalizability of the two models being the Altman Z-score (1968) and the Altman Z”-score (1993) in the Jordanian environment. The sample tested consisted of 71 failed and 71 non-failed companies. The financial statements (balance sheet and income statement) were gathered for three full years for each tested company. The Z-score was applied to industrial and service companies and the Z” score was only applied on service firms. The original Altman Z-score (1968) was proven to be generalizable in Jordan, where it was able to predict failed industrial companies. Both the Altman Z-score (1968) and the Altman Z”-score (1993) had low predictive abilities for service firms. The re-estimation of the models’ coefficients using the Multivariate Discriminant Analysis in the context of Jordan was not possible, since predictors of the models violated the normal distribution assumption (Alareeni & Branson, 2012).

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The purpose of the article is to educate the readers (entrepreneurs) on how to they can reliably predict the bankruptcy of their businesses (or a supplier's business) two years in advance, giving them time to minimize losses. Thus, this also concerns parties lending funds, potential investors or anyone involved in setting goals for the company. In 1968, Altman (Assistant Professor of Finance at New York University) published his formula. He compared a group of bankrupt firms with a set of similar sized solvent firms from the same size. He then applied the statistical method of discriminant analysis to reach a linear combination of five common business ratios weighted by coefficients. His formula shows to be 80-90% accurate at predicting bankruptcy one year before the event. The risk of a false positive (predicting bankruptcy which doesn't then happen) is estimated at 15% to 20%. Since the analysis of published financials provides little understanding regarding what changes in management were implemented in order to survive their bankruptcy prediction, the author's personal hypothesis is that what the false positives really show is that 15% to 20% of firms heading for bankruptcy can fight their way out of it given advance warning, however there is no data to back this up. It is worth mentioning that the Z-Score differs for manufacturing and non-manufacturing firms, as well as those privately held. It's not suitable for financial services since generally they have structured their assets and liabilities into special purposes. The Z' score formula tested is the modified version for private firms. The results signify the following:

Z' > 2.9 - "Safe" Zone: you are highly unlikely to go under any time soon.

1.23 < Z' < 2.9 - "Grey" Zone: the closer you are to a score of 1.23 the more likely you are to be in serious financial difficulty.

Z' < 1.23 - "Distress" Zone: 80%-90% of firms in this zone will go bankrupt within a year; ±15% of the firms in this zone won't.

- Concerning practical application, the formula can be used by the business owner to take preventive actions early on, by the credit extender to limit the facilities given to the client, by the investor to evaluate the problems and risks he is incurring if he decides to invest in the subject business. If the z-score is applied to the supplier, the business owner can seek different suppliers if results did not provide comfort (Gareth Ochse, 2013).

Other researchers from Latvia evaluated seven bankruptcy prediction models on Baltic companies being the Altman Z'-score, the Altman Z''-score, the Altman Z-score model, the Sorin-Voronova model, the Zmejewski model, the Fulmer model, and the Springate model. The sample of the study consisted of 75 companies listed on the Baltic Stock Exchange, over the period 2002-2011. It is worth noting that a greater number of factors don't necessarily increase the model accuracy. Type I error is identified as the misclassification of bankrupt firms as non-bankrupt, and Type II error is the misclassification of non-bankrupt firms as bankrupt.

The following findings were drawn from the study: first, although the performance of bankruptcy prediction models is important, particularly during the changing economic conditions, it is uncertain whether any model is able to generate good results during economic downturns. Second, good outcomes are achieved by Altman Z' and Altman Z'' models during the economic growth phase. Third, the results of correlation analysis (Pearson correlation matrix) show a direct positive relationship between type II errors of all model, meaning the increase (decrease) of type II for one model, is reflected by the same increase (decrease) for the other models. Finally, this study was found relatively consistent with previous studies in Latvia regarding the same subject. Some differences exist are probably due to different sampling (Berzkalne & Zelgalve, 2013).

A study conducted on 89 bankrupt Italian companies (52 of the sample were manufacturing companies), which are subject to Extraordinary Administration, a bankruptcy filing chapter in Italy, applies the Z-Score to the financial statements of Italian companies between 2000 and 2010. The author indicates that the model is not probabilistic but rather descriptive-comparative, meaning that it should be used as a warning device rather than as a definitive prediction tool. The Z"-Score was chosen to be tested for several reasons: only four companies (less than 5% of those subjected to EA) were public, the Z"-Score prediction tool is more suitable for the Italian context than the Z'-Score, taking into consideration that many of the firms subject to EA were not manufacturers, and because it has been shown that the Z"-Score model applied to non-US companies is more robust than his other models. The control sample consists of around 1,575 manufacturing companies active between 2001 and 2009. During the application, the central problem faced was the cultural and economic differences between US and Italy. The Altman Z”-score was chosen to be tested noting that it is used for manufacturing and non-manufacturing sectors operating in developing countries. For the calculation of the Z" Score for emerging countries, Altman, Hartzell and Peck (1995) suggested to add a constant (+3.25) to standardize the results; which will allow the scores less than or equal to zero to be equivalent to the default area. The Z score was calculated for each of the 5 years before declaring bankruptcy, and the results showed that on average, over the whole five years prior to bankruptcy, in 72.3% of the cases (which increases to 77.8% if the results from year 5 from bankruptcy are excluded), the classifications of the indicator are correct. As for the control sample, more than 50% of the control sample's firms are classified inside the safe zone. This percentage remains relatively stable; noting that the average of firms in the safe zone dropped from 51% in 2008 to nearly 49% in 2009, underlining the negative effects of the credit crisis on the Italian market in 2008.

The authors concluded that Altman's Z"-Score model can be applied to the Italian manufacturing context but with a few cautions: in case the balance sheet figures are manipulated, the model can't identify distress situations, furthermore, the study showed that the parameters can be reformulated based on the characteristics of Italian companies, (i.e. low capitalization, heavy use of bank credit and sometimes ambiguous budget policies) (Altman, Danovi, and Falini, 2013).

Banks are extremely important actors in the financial systems globally, thus their failures have more significant effects than the failure of non-financial enterprises. Some of the early signs of distress of banks are: increase in the number of non-performing loans, continuous decrease in earnings per asset, high staff turnover, consistent sourcing of funds from the interbank market, withdrawals of depositors, more fraud incidents, inability to comply with statutory requirements, and instability of corporate management. In fact, success of corporations is highly dependable on management quality. Concerning the authors' field of study which is the Nigerian banking sector, it has witnessed since 1930 signs of distress; where 21 banks failed between 1930 and 1958, and 31 banks had their licenses revoked between 1994 and 1998 because they failed to meet statutory minimum capital requirements. The distress in the Nigerian banking sector had many negative effects on the whole economy: loss of public confidence in financial system, loss of savings, loss of investment, increased unemployment, and loss of national productivity and output. These consequences affected all the other actors in the economy, namely the government, regulatory authorities, and the general public. Related literature examined and rated the banks using five standards: capital adequacy, assets quality, management competency, earnings strength, and liquidity sufficiency. Generally, business failure models can be divided to two categories which are qualitative and quantitative models. Qualitative models are based on non-accounting variables. In this subject, Argenti (2003) created the A score, suggesting that the failure process follows a specific sequence: defects, mistakes, symptoms of failure. On the other hand, quantitative models use commonly-accepted financial indicators of failure, including low profitability related to assets and commitments low equity returns, both dividend and capital, poor liquidity high gearing high variability of income. One of the widely used quantitative models is the Altman Z-score which consists of ratios measuring profitability, liquidity, and solvency. The original the Z–Score model was developed for public manufacturing firms and eliminated all firms with assets less than $1 million, since it was not intended for small, nonmanufacturing, or non-public companies, although many credit granters today still use the original Z score for all types of customers. Two further prediction models were formulated by Altman (sometimes referred to as model ‘A’ and model ‘B’ to the original Z score (Altman, 1968). The model ‘A’ z-score was developed for use with private manufacturing companies, while model ‘B’ was developed for private general firms, noting that both of these models differ from the original model and from each other in terms of weights of the ratios, the ratio related to the value of equity and the scoring. Previous studies of the z-score considered the simplicity and low cost of the z-score. Also, studies related to the failure of five Nigerian banks found the Altman z-score to be a significant prediction index, and together with management competency are critical to measuring the health state of Nigerian banks.

- Regarding the author's research, it analyzed the audited accounts of banks for the period 2006-2012 and generated the financial ratios used in the Altman Model. The population consists of ten selected banks listed in Nigerian Stock Exchange (Access Bank plc, Diamond Bank plc, Fist City Monument Bank plc, Fidelity Bank plc, GT Bank plc, Skye Bank plc, United Bank of African plc, Union Bank plc, Wema Bank plc, and Zenith Bank plc).
- The researchers used Altman's original model for public companies. They want to test the hypothesis that the Altman Z-score model could have predicted the failure of ten of the currently bankrupt Nigerian banks. The data required include: working capital, retained earnings, earnings before interest and tax, equity as well as total assets and total book debts. The results were illustrated in a table, showing for each of the ten banks the results of the Z-score for the seven years understudy, in addition to the individual score of each of the financial ratios constituting the z-score formula for the same period. All the banks during all the years showed z-scores below 1.81, indicating that they are in the bankruptcy region, except for 2 banks which generated z-scores above 1.81 for one year each (Zenith Bank, a score of 3.86 for 2008, and GTB, with a score of 1.867 for 2010), noting that after these years, their scores dropped again below 1.81. Accordingly, the study accepts the alternative hypothesis which stated that Altman bankruptcy prediction model could have successfully predicted the failure of the banks that actually went bankrupt in the Nigerian banking sector.
- Finally, the findings of the study are the following:

- 1. The model was capable of measuring accurately the failure potential of once sound and healthy banks, thus it could have successfully predicted the failure of the banks that actually went under in the Nigerian banking sector.

- 2. The results show that most of these healthy banks are under bankruptcy region and undetected by the regulatory authority.

- 3. Therefore, the levels of Capital adequacy; Assets quality; and Liquidity sufficiency are critical indices for measuring the health state of banks in Nigeria as earlier suggested by Altman.

The authors consequently recommend that the regulatory authority make the necessary efforts to domesticate Altman's model in order to monitor of the health of Nigerian banks. Another solution would be to develop a separate model which takes into consideration the unique Nigerian environment using basic principles similar to those used for the z-score model (Ezejiofor, Nzewi, and Okoye, 2014).

The second part of the literature review presents the papers which identified the financial ratios that are significantly different between bankrupt and solvent companies, and some of these papers developed bankruptcy prediction models using those financial ratios as independent variables.

In the subject of prediction of bankruptcy through financial ratios, 6 university students from Romania meant to expose the deficiencies of the rating systems in the Romanian banking sector, resulting in flawed judgment of the credit files. Eighteen indicators are tested for significance: ROE, ROA, ROS, Customer Rotation Speed, Customer Rotation Time, Assets Rotation Speed, Equity Ratio, Indebtedness, Solvency, Liabilities Cover, Fixed Assets Cover, Capital Ratio, Current Assets Ratio, Liquid Assets, Total Balance Sheet, Net Income, Fixed Assets Return, and Short Term Cover. The sample of this study consists of 3000 companies (solvent and non-solvent) in the county Mures. Their financial statements were gathered for the period 1999-2008. For each year, the percentage of defaulted companies to the total number of companies tested is calculated. To identify the significant indicators of the solvency of companies, the T-test method was calculated. The test was applied on the assumption that the standard deviations of bankrupt and non-bankrupt companies were matching: this is tested using the F-test with a significance level of 5%. During the studied ten years, eight ratios proved to be significant: the ROA eight times (meaning 8 years out of the 10 years, the index was significant), the assets rotation speed nine times, own equity ratio five times, debt rate six times, current asset ratio five times, liquid assets five times as well, total balance sheet eight times, and net income was significant only in one year. The other ten variables were not proven significant, thus cannot be used to predict bankruptcy (Kovács, Dóczi, Erdély, Falfalusi, Knoch & Patka, 2011).

Similar researches in Poland aimed to develop models that can corporate predict bankruptcy, using the financial ratios of the subject company. The sample consists of 41 legally bankrupt companies and 41 healthy companies, and 15 financial ratios were selected to be tested for difference: load of enterprise by current liabilities (current liabilities / total liabilities), return on assets (net profit / total assets), return on sales (net profit / sales income), share of liabilities in total assets (receivables / total assets), share of intangible assets in total assets (intangible assets / total assets), share of tangible assets in total assets (tangible assets / total assets), share of fixed assets in total assets (fixed assets / total assets), current ratio (current assets / current liabilities), long term debt ratio (long term liabilities / equity capital), employment of working capital funds (sales income / working capital), debt equity ratio (total liabilities / equity), total debt ratio (total liabilities / total assets), total involvement liabilities ratio (sales income / total liabilities), share of inventories in total assets (total inventories / total assets), ability to repay a debt (net income + depreciation/ total liabilities). The most predictive ratios were selected using the forward and backward method, being the return on sales, the share of fixed assets in total assets, the employment of working capital funds, the total involvement liabilities ratio, ability to repay a debt, ROA, current ratio, long term debt ratio, total debt ratio, and share of inventories in total assets. Two models using the logistic regression were developed and two models using the discriminant analysis were developed, and these models were tested on the initial sample, and then the results were validated on a sample of 16 companies (8 bankrupt, 8 healthy). The models using the logistic regression produced higher accuracy rates than the models using discriminant analysis, with results ranging from 88.89% to 94.4% accuracy (vs. 50% to 89.02% accuracy for discriminant analysis models) (Waszkowski, 2011).

Other researchers in Thailand tested the difference of 22 financial ratios when applied on 199 failed firms and 398 non-failed firms. The financial ratios tested are from the following categories: Liquidity (Cash/Total Assets, Cash/Current Liabilities, Current Assets/Current Liabilities, Current Liability/Total Assets, Working Capital/Total Assets, and Working Capital/Total Liabilities), Leverage (Current Liability/Total Equity, Total Equity/Total Liability, Total Liability/Total Equity, Long-Term Liability/Total Assets, Total Liabilities /Total Assets and Total Equity/Total Asset), Activity (Sales/Current Assets, Sales/Total Assets, Operating Income/Total Assets and EBT/Total Equity), and Profitability (EBT/Total Assets, Net Income/Sales, Net Income/Total Assets, Net Income/Total Equity, EBITDA/Total Assets, and EBIT/Total Assets). After applying the test of equality of means and the multicollinearity test, the 8 financial ratios that passed the two test are selected (Cash/Total Assets, Working Capital/Total Assets, Current Liability/Total Equity, Long-Term Liability/Total Assets, Total Liabilities /Total Assets, Operating Income/Total Assets, EBT/Total Assets and Net Income/Sales) to develop the 2 models, one using the Multivariate Discriminant Analysis, the other one using the logistic regression. Four models are created using the SPSS: 2 models using the MDA (one composed of 6 financial ratios, the other composed of 3 financial ratios and 2 categorical variables, being two years loss for bankrupt companies and three years profit for solvent companies), and 2 models using the logistic regression (one composed of 6 financial ratios, the other composed of 3 financial ratios and 2 categorical variables, being two years loss for bankrupt companies and three years profit for solvent companies). The highest predictive accuracy was achieved by the logistic regression using only financial ratios, with an R squared of 85.5% for out-of-sample test (Sirirattanaphokun and Pattarathammas, 2012).

Research in Romania created models using the Multivariate Discriminant Analysis and the Logistic regression to assess the corporate bankruptcy prediction ability of financial ratios. The sample consisted of 100 companies, 50 in viable and 50 bankrupt. In this study, a company was considered bankrupt if it had difficulties in honoring its obligations to creditors or did not honor them at all, in other words, bankrupt was considered equivalent to insolvent. The financial statements of the companies were gathered for the years 2007 to 2011. To select the independent variables of the models, fourteen financial indicators from 5 different categories (each category interested a specific group of stakeholders) were tested for difference between the bankrupt companies and the viable companies: rates of return category which interested shareholders and managers included the profit rate, ROA, ROE and profit per employee, the rates of liquidity useful to short term creditors included the current ratio and quick ratio, the rates of debt which are important to the capital providers included the debt to equity ratio and total debt to total assets, rates of activity which interests managers and third parties included inventory, receivables and total assets turnover, and additional economic and financial information included the log of total assets (representing the company's size), the log of total assets ratio to total employees (expressing the use of assets by employees) and the log of ratio operating income to total employees (representing the revenues obtained by employees), noting that the logarithm was applied to bring all values to a similar scale. The means of each of the 14 financial indicators were calculated for the 2 groups (bankrupt and viable) for the years 2007 until 2011, and a cumulative result was also calculated for the three years 2009, 2010 and 2011. To select the indicators that best represent the information gathered for each year from the pool of 14 indicators, the Principal Component Analysis was used on SPSS. Three indicators were eliminated (the profit per employee, the log of total assets ratio to total employees and the log of ratio operating income to total employees). Using the MDA, a model for each year was created, in addition to a model for the cumulative 2009-2011. The same procedure was done using the Logistic regression. The models were applied on the initial sample to conduct the apriori analysis. The cumulative function for the three years achieves the highest accuracy results (96% for MDA and 84% for logistic regression). In the aposteriori analysis, which consists of applying the models of another sample of similar firms (total of 40 companies, 20 bankrupt and 20 viable), further reveals the accuracy of the cumulative function (95% for MDA and 82% for logistic regression). The author concludes that the MDA is the best predictor of the Romanian market (Onofrei, 2014).

2.2 Summary of Literature Review

The subject of bankruptcy prediction is international. Bankruptcy has a legal definition of filing for bankruptcy, and a financial definition of defaulting on obligations or having a poor account movement. The main approaches used to predict bankruptcy are: the application of existing prediction models and the identification of significant financial ratios which leads to the development of bankruptcy prediction models.

The most applied models worldwide are the Altman models, which are mainly three models: the original Altman Z-score, the Altman Z’ score and the Altman Z” score. Altman’s original Z-score model was created in 1968, and was meant to be applied on manufacturing companies with a capital of over $ 1 million. Altman’s Z’-score and Z”-score were later derived from the original Z-score, each one with an attuned formula to a specific type of companies. The Z’-score is meant to be applied on privately-held manufacturing firms and the Z”-score is for both public and private non-manufacturing firms. Other models such as the Kida model the Conan-Holder model, the Taffler model, the Anghel model, Sorin-Voronova model, the Zmejewski model, the Fulmer model, and the Springate model were also tested. Accuracy levels are considered high when they reach 80-90% accuracy.

The second approach consists of testing the financial ratios for their predictive ability. A financial ratio is considered significant when its mean for financially healthy companies is significantly different from its mean for the financially unhealthy companies. This is tested using the independent sample t-test. The financial ratios tested in the literature review are from different categories: liquidity, profitability, leverage, activity.

The third approach is to develop a customized model for the sample under study using significant financial ratios. In the literature review, two statistical methods were used: the Logistic Regression and the Multivariate Discriminant Analysis. The former is preferable due to the fewer assumptions needed. The Logistic Regression generates an outcome in terms of odds ratio.

Based on the above literature review, I structured my thesis. Since all the papers specified that the most internationally tested models are the Altman Models, yielding the highest levels of accuracy worldwide compared to other models, I decided to apply Altman’s Z scores in Lebanon as a first approach. As already mentioned, the Altman Z’ and Altman Z” were selected for their applicability on Lebanese companies, in contrast with the original Altman Z score. For the second approach, I will study the significant financial ratios in Lebanon, as done by many papers in the literature review. the financial ratios tested in these papers, which are applicable on the financial statements of the SMEs in Lebanon will be tested. The third approach is to structure a logistic regression model using jointly significant financial ratios. This was done in several countries, since it provides a customized view for each country rather than applying an international model.

CHAPTER THREE
RESEARCH FRAMEWORK AND METHODOLOGY

3.1 Research Questions

I would like to explore whether the state of SMEs in Lebanon can be predicted solely by its financial ratios, through three different approaches. Therefore my research questions are the following:

- To evaluate the bankruptcy prediction ability of the models tested (the Altman Z'-score, Altman Z"-score) on the selected SMEs in Lebanon.
- To determine if the financial ratios of defaulted SMEs (non-performing loans) and solvent SMEs (performing loans) are statistically significantly different from each other.
- To determine if the estimated logistic regression models can accurately predict the classification of performing loans and non-performing loans of SMEs in Lebanon.

3.2 Hypotheses

Hypothesis 1: the Altman Z-scores can accurately predict the classification of SMEs (performing loans/non-performing loans) in Lebanon.

Hypothesis 1a – The Altman Z'-score can accurately predict performing and non-performing loans for manufacturing SMEs in Lebanon.

Hypothesis 1b – The Altman Z''-score can accurately predict performing and non-performing loans for non-manufacturing SMEs in Lebanon.

*A model that can predict bankruptcy is the one that achieves high percentage of accuracy in the classification of both solvent companies and bankrupt companies, resulting in low type I and type II errors.

Hypothesis 2– There are significant differences between the financial ratios of SMEs subject to performing loans versus the SMEs subject to non-performing loans in Lebanon.

(There are 22 sub-hypotheses for Hypothesis 2, being one for each financial ratio tested).

*The significant ratios are the ones that register p-values lower than 5% in the independent sample t-test.

Hypothesis 3– The estimated models using the logistic regression can accurately predict the classification of performing loans and non-performing loans for SMEs in Lebanon.

*A model that can predict bankruptcy is the one that achieves high percentage of accuracy in the classification of both solvent companies and bankrupt companies, resulting in low type I and type II errors.

3.3 Methodology

3.3.1 Instrument

The instrument used in this study is data analysis developed by the researcher based on related literature and concepts.

The financial statements of SMEs in Lebanon, being Balance Sheet, Income Statement and Ratios Sheet, were extracted from the dataset of a Bank in Lebanon.

3.3.2 Sample Size

The sample size includes 222 SMEs, of which 187 are subject to performing loans and 35 subject to non-performing loans. From the total number of companies, 63 are manufacturing companies and 159 are non-manufacturing companies.

Concerning the criteria of having the financial statements audited or non-audited, 126 of the total SMEs in non-audited while 96 are audited.

3.3.3 Type I and Type II errors

The type I error is misclassifying solvent companies as bankrupt. The type II error is misclassifying the bankrupt companies as solvent. In this case, the type II error is the more dangerous, since it would lead to a defaulted loan because an actually bankrupt company was classified as solvent and accordingly it was granted a loan on which it will default. However, the type I error is only a missed opportunity of lending a financially healthy SME a loan that it will repay on time, because it was misclassified as bankrupt.

CHAPTER FOUR

STATISTICAL ANALYSES

The 22 financial ratios and indicators which will be tested in the study are selected from the literature review, based on their applicability on the financial statements of the SMEs in Lebanon, noting that several additional ratios were worth testing however they are not applicable on the available data. First, the means of the 22 ratios are presented for the years 2011, 2012 and the average between the 2 years, divided between bankrupt and solvent.

(Table 1)

Ratio	Mean 2011		Mean 2012		Mean Average	
	Bankrupt	Solvent	Bankrupt	Solvent	Bankrupt	Solvent
Net Income/Equity	1.28	0.31	1.46	0.32	1.37	0.31
Liabilities/Equity	7.27	0.62	-5.86	0.62	0.70	0.62
Equity/Fixed Assets	40.18	2.34	29.75	2.7	34.96	2.52
Current assets/Total assets	0.34	0.42	0.32	0.42	0.33	0.42
Log of total assets	13.5	13.76	13.28	13.91	13.39	13.84
Net Income/Fixed assets	9.31	1.06	8.19	1.3	8.75	1.18
Liquid assets* /Current assets	0.58	0.45	0.57	0.45	0.57	0.45
Fixed assets/Total assets	0.66	0.58	0.68	0.58	0.67	0.58
Current assets/Current liabilities	2.16	9.14	1.31	4.49	1.74	6.81
Current Liabilities/Equity	2.75	0.28	-3.49	0.3	-0.37	0.29
Total liabilities/Total	0.55	0.27	0.6	0.28	0.58	0.28

assets						
Total equity/Total assets	0.45	0.73	0.4	0.72	0.42	0.72
Sales/Current assets	6.91	4.36	45.11	4.29	26.01	4.33
Net income/Sales	0.12	0.22	-0.17	0.21	- 0.02	0.22
Current liabilities/Total liabilities	0.51	0.61	0.57	0.6	0.54	0.61
Receivables/Total assets	0.14	0.12	0.12	0.13	0.13	0.13
Sales/Liabilities	2.97	16.01	2.6	8.31	2.79	12.16
Working capital/Assets	0.11	0.27	0.01	0.28	0.06	0.27
Retained Earnings/Assets	0.16	0.18	0.14	0.2	0.15	0.19
EBIT/Assets	0.18	0.27	0.14	0.21	0.16	0.24
BV equity/BV liabilities	1.72	33.83	1.43	19.91	1.58	26.87
Sales/Total assets	0.96	1.26	0.98	1.24	0.97	1.25

*Liquid assets are the current assets minus the inventory.

The above table implies the following:

- Net Income/Equity is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Liabilities/Equity is lower in absolute value for bankrupt SMEs than for solvent SMEs in Lebanon.

- Equity/Fixed Assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Current assets/Total assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Log of total assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Net Income/Fixed assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Liquid assets* /Current assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Fixed assets/Total assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Current assets/Current liabilities is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Current Liabilities/Equity is higher in absolute value for bankrupt SMEs than for solvent SMEs in Lebanon.

- Total liabilities/Total assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Total equity/Total assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Sales/Current assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon.

- Net income/Sales is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Current liabilities/Total liabilities is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Receivables/Total assets is higher for bankrupt SMEs than for solvent SMEs in Lebanon in 2011, lower in 2012 and equal in the average of both years.

- Sales/Liabilities is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Working capital/Assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Retained Earnings/Assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- EBIT/Assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- BV equity/BV liabilities is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

- Sales/Total assets is lower for bankrupt SMEs than for solvent SMEs in Lebanon.

The ratios can be divided by categories as follows:

- Liquidity: Working capital/Assets, Receivables/Total assets, Liquid assets /Current assets, Current assets/Current liabilities, Fixed assets/Total assets, Current assets/Total assets.
- Leverage: Current liabilities/Total liabilities, BV equity/BV liabilities, Total equity/Total assets, Total liabilities/Total assets, Current Liabilities/Equity, Liabilities/Equity, Equity/Fixed Assets.

- Activity: Sales/Liabilities, Sales/Total assets, Sales/Current assets.

- Profitability: Net income/Sales, EBIT/Assets, Retained Earnings/Assets, Net Income/Fixed assets, Net Income/Equity.

Altman Models:

The tables below illustrate the accuracy results of the Altman formulas. Each formula is assessed based on its ability to accurately predict the state of each company. The first table is in percentage terms while the second is in frequency terms.

(Table 2)

	Altman Z'2011	Altman Z'2012	Altman Z"2011	Altman Z"2012	Altman Z' average	Altman Z" average
fail within bankrupt	34.3%	34.3%	25.7%	40.0%	40.0%	25.7%
grey within bankrupt	31.4%	34.3%	17.1%	11.4%	28.6%	22.9%
no fail within bankrupt	34.3%	31.4%	57.1%	48.6%	31.4%	51.4%
total	100%	100%	100%	100%	100%	100%
fail within solvent	0.5%	2.1%	2.1%	1.6%	1.6%	1.6%
grey within solvent	32.1%	28.9%	4.8%	4.8%	28.9%	4.3%
no fail within solvent	67.4%	69.0%	93.0%	93.6%	69.5%	94.1%
total	100%	100%	100%	100%	100%	100%

(Table 3)

fail within bankrupt	12	12	9	14	14	9
grey within bankrupt	11	12	6	4	10	8
no fail within bankrupt	12	11	20	17	11	18
total	35	35	35	35	35	35
fail within solvent	1	4	4	3	3	3
grey within solvent	60	54	9	9	54	8

no fail within solvent	126	129	174	175	130	176
total	187	187	187	187	187	187

The results are displayed in the below tables for a clearer display.

<u>The first row:</u>

The first cell (actual/bankrupt-prediction/bankrupt) indicates the percentage of actually bankrupt companies that were accurately classified by the Altman model as bankrupt. The second cell (actual/bankrupt-prediction/solvent) indicates the percentage of actually bankrupt SMEs inaccurately classified as solvent, which is the type II error. The third cell (actual/bankrupt-prediction grey area) is the percentage of bankrupt companies classified in the grey area.

<u>The second row:</u>

The first cell (actual/solvent-prediction/bankrupt) is the percentage of actually solvent SMEs, inaccurately classified as bankrupt, which is the type I error. The second cell (actual/solvent-prediction/solvent) represents the actually solvent SMEs accurately classified as solvent. The third cell (actual/solvent-prediction grey area) is the percentage of solvent SMEs classified in the grey area.

As mentioned earlier, the type I error is misclassifying solvent companies as bankrupt, and the type II error is misclassifying the bankrupt companies as solvent. The type II error is the more dangerous, since it would lead to a defaulted loan, while the type I error is merely a missed opportunity of lending a financially healthy SME.

Altman Z' score 2011:

(Table 4)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	34.3% (no error)	34.4% (type II)	31.3%	100%
	Solvent	0.5% (type I)	67.4% (no error)	32.1%	100%

Altman Z' score 2012:

(Table 5)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	34.3% (no error)	31.4% (type II)	34.3%	100%
	Solvent	2.1% (type I)	69% (no error)	28.9%	100%

Altman Z' score average:

(Table 6)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	40% (no error)	31.4% (type II)	28.6%	100%
	Solvent	1.8% (type I)	69.5% (no error)	28.7%	100%

Altman Z" score 2011:

(Table 7)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	25.7% (no error)	57.1% (type II)	17.2%	100%
	Solvent	2.1% (type I)	93% (no error)	4.9%	100%

Altman Z" score 2012:

(Table 8)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	40% (no error)	48.6% (type II)	11.4%	100%
	Solvent	1.6% (type I)	93.6% (no error)	4.8%	100%

Altman Z" score average:

(Table 9)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	25.7% (no error)	51.4% (type II)	22.9%	100%
	Solvent	1.6% (type I)	94.1% (no error)	4.3%	100%

In the following tables, each formula is calculated on the specific type of companies it targets, *Z'* for manufacturing companies (i.e: furniture, wood products, steel products, food items…), *Z"* for non-manufacturing companies (i.e.: agriculture, restaurants, gas stations, pharmacies, retail and wholesale trade of various products…). The first table is in percentage terms while the second is in frequency terms.

(Table 10)

	Altman Z'2011 (m)	Altman Z'2012 (m)	Altman Z"2011(nm)	Altman Z"2012(nm)	Altman Z'average (m)	Altman Z"average (nm)
fail within bankrupt	0.0%	14.3%	28.6%	35.7%	14.3%	25.0%
grey within bankrupt	42.9%	57.1%	17.9%	10.7%	57.1%	25.0%
no fail within bankrupt	57.1%	28.6%	53.6%	53.6%	28.6%	50.0%
total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
fail within solvent	1.8%	5.4%	2.3%	1.5%	5.4%	1.5%
grey within solvent	35.7%	33.9%	3.8%	3.8%	33.9%	3.1%
no fail within solvent	62.5%	60.7%	93.9%	94.7%	60.7%	95.4%
total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

(Table 11)

	Altman Z'2011 (m)	Altman Z'2012 (m)	Altman Z"2011 (nm)	Altman Z"2012 (nm)	Altman Z'average (m)	Altman Z"average (nm)
fail within bankrupt	0	1	8	10	1	7
grey within bankrupt	3	4	5	3	4	7
no fail within bankrupt	4	2	15	15	2	14
total	7	7	28	28	7	28
fail within solvent	1	3	3	2	3	2
grey within solvent	20	19	5	5	19	4
no fail within solvent	35	34	123	124	34	125
total	56	56	131	131	56	131

(Table 12)

total manufacturing bankrupt	total manufacturing solvent	total non-manufacturing bankrupt	total non-manufacturing solvent		total manufacturing	total non-manufacturing	Total
7	56	28	131		63	159	222

As in the previous section, the results are classified in the tables below to better illustrate the accuracy levels of the models tested.

Altman Z' score 2011 (manufacturing):

(Table 13)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	0% (no error)	57.1% (type II)	42.9%	100%
	Solvent	1.8% (type I)	62.5% (no error)	35.7%	100%

Altman Z' score 2012 (manufacturing):

(Table 14)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	14.3% (no error)	28.6% (type II)	57.1%	100%
	Solvent	5.4% (type I)	60.7% (no error)	33.9%	100%

Altman Z' score Average (manufacturing):

(Table 15)

Prediction

Actual		Bankrupt	Solvent	Grey area	Total
	Bankrupt	14.3% (no error)	28.6% (type II)	57.1%	100%
	Solvent	5.4% (type I)	60.7% (no error)	33.9%	100%

Altman Z” score 2011 (non-manufacturing):

(Table 16)

Prediction

Actual

	Bankrupt	Solvent	Grey area	Total
Bankrupt	28.6% (no error)	53.6% (type II)	17.8%	100%
Solvent	2.3% (type I)	93.9% (no error)	3.8%	100%

Altman Z” score 2012 (non-manufacturing):

(Table 17)

Prediction

Actual

	Bankrupt	Solvent	Grey area	Total
Bankrupt	35.7% (no error)	53.6% (type II)	10.7%	100%
Solvent	1.5% (type I)	94.7% (no error)	3.8%	100%

Altman Z” score Average (non-manufacturing):

(Table 18)

Prediction

Actual

	Bankrupt	Solvent	Grey area	Total
Bankrupt	25% (no error)	50% (type II)	25%	100%
Solvent	1.5% (type I)	95.4% (no error)	3.1%	100%

Independent Sample T-Test:

The second step of this study is to determine which financial ratios of the 22 financial ratios tested, is individually significantly different between bankrupt and solvent Lebanese SMEs. The financial ratios that are significantly different are the most predictive of the state of a company.

The significant of these ratios was tested through the independent sample T-test, applied o the years 2011, 2012 and on the average of these two years.

The test consists first of determining if equal variances are assumed or not, with H0 = variances between bankrupt and solvent companies are equal, and H1 = variances between bankrupt and solvent companies are not equal. If the p-value for this test is less above 0.05, then we fail to reject the null and equal variances are assumed. If the p-value is less than 0.05, then we reject the null and unequal variances are assumed.

Second, based on the variances being equal or not, the p-value of each ratio is selected. the null hypothesis here is that p-value of the ratio is greater than 0.05, meaning that the ratio is the same for bankrupt and solvent companies. H1 is that the p-value is less than 0.05, meaning that the ratio is significantly different for bankrupt and solvent companies.

The results, illustrated in the below table, show the following:

- Liabilities/Equity was significantly different between bankrupt and solvent SMEs in 2011.
- Current assets/Total assets was significantly different between bankrupt and solvent SMEs in 2012.
- Log of total assets was significantly different between bankrupt and solvent SMEs in 2012 and the average of the years 2011 and 2012.

- Liquid assets/Current assets was significantly different between bankrupt and solvent SMEs in 2011, 2012 and the average of the years 2011 and 2012.
- Fixed assets/Total assets was significantly different between bankrupt and solvent SMEs in 2012.
- Current assets/Current liabilities was significantly different between bankrupt and solvent SMEs in 2012 and the average of the years 2011 and 2012.
- Total liabilities/Total assets was significantly different between bankrupt and solvent SMEs in 2011, 2012 and the average of the years 2011 and 2012.
- Total equity/Total assets was significantly different between bankrupt and solvent SMEs in 2011, 2012 and the average of the years 2011 and 2012.
- Sales/Total Liabilities was significantly different between bankrupt and solvent SMEs in 2011, 2012 and the average of the years 2011 and 2012.
- Working capital/Total assets was significantly different between bankrupt and solvent SMEs in 2011, 2012 and the average of the years 2011 and 2012.

Since the ratios current assets/total assets and fixed assets/total assets, and the ratios liabilities/assets and equity/assets are complimentary (their sum is equal to 1), the significance of one of the ratios will certainly mean that the other ratio is also significant.

The below is a detailed table showing all the results. The results highlighted in yellow are the p-values that are considered. The p-values highlighted in green are the ones below 0.05, indicating the significance of the related financial ratio.

(Table 19)

Variable	Variance equality	Levene's Test for Equality of Variances		T-test for equality of means		
		F	Sig.	t	df	Sig. (2-tailed)
netincomeOequity2011	Equal variances assumed	19.189	.000	2.370	220	.019
	Equal variances not assumed			1.020	34.025	.315
netincomeOequity2012	Equal variances assumed	34.369	.000	3.150	220	.002
	Equal variances not assumed			1.358	34.032	.183
avernetincomeOequity	Equal variances assumed	40.797	.000	3.335	220	.001
	Equal variances not assumed			1.440	34.040	.159
liabilitiesOequity2011	Equal variances assumed	86.049	.000	5.015	220	.000
	Equal variances not assumed			2.168	34.045	.037
liabilitiesOequity2012	Equal variances assumed	20.217	.000	-1.330	220	.185
	Equal variances not assumed			-.570	34.003	.572
averliabilitiesOequity	Equal variances assumed	18.209	.000	.032	220	.974
	Equal variances not assumed			.014	34.011	.989
equityOfixedassets2011	Equal variances assumed	21.902	.000	2.246	220	.026
	Equal variances not assumed			.963	34.005	.342
equityOfixedassets2012	Equal variances assumed	20.887	.000	2.154	220	.032
	Equal variances not assumed			.927	34.022	.361
averequityOfixedassets	Equal variances assumed	21.488	.000	2.207	220	.028
	Equal variances not assumed			.948	34.011	.350
currentassetsOtotalassets2011	Equal variances assumed	3.126	.078	-1.518	220	.130
	Equal variances not assumed			-1.356	43.623	.182
currentassetsOtotalassets2012	Equal variances assumed	1.319	.252	-2.045	220	.042
	Equal variances not assumed			-1.848	43.965	.071
avercurrentassetsOtotalassets	Equal variances assumed	2.304	.130	-1.797	220	.074
	Equal variances not assumed			-1.610	43.724	.114
logtotalassets2011	Equal variances assumed	.226	.635	-1.102	220	.272
	Equal variances not assumed			-1.265	54.990	.211
logtotalassets2012	Equal variances assumed	7.418	.007	-3.203	220	.002
	Equal variances not assumed			-2.029	37.040	.050
averlogtotalassets	Equal variances assumed	2.585	.109	-2.246	220	.026
	Equal variances not assumed			-1.829	41.210	.075
netincomeOfixedassets2	Equal variances assumed	19.340	.000	2.125	220	.035

011	Equal variances not assumed			.921	34.057	.364
netincomeOfixedassets2	Equal variances assumed	16.723	.000	1.936	220	.054
012	Equal variances not assumed			.864	34.208	.393
avernetincomeOfixedass	Equal variances assumed	18.221	.000	2.040	220	.043
ets	Equal variances not assumed			.894	34.114	.377
liquidassetsOcurrentass	Equal variances assumed	.403	.526	2.580	220	.011
ets2011	Equal variances not assumed			2.386	44.713	.021
liquidassetsOcurrentass	Equal variances assumed	.395	.530	2.282	220	.023
ets2012	Equal variances not assumed			2.128	44.985	.039
averliquidassetsOcurren	Equal variances assumed	.291	.590	2.469	220	.014
tassets	Equal variances not assumed			2.282	44.688	.027
fixedassetsOtotalassets	Equal variances assumed	3.029	.083	1.523	220	.129
2011	Equal variances not assumed			1.363	43.674	.180
fixedassetsOtotalassets	Equal variances assumed	1.328	.250	2.042	220	.042
2012	Equal variances not assumed			1.845	43.966	.072
averfixedassetsOtotalas	Equal variances assumed	2.269	.133	1.798	220	.074
sets	Equal variances not assumed			1.613	43.754	.114
currentassetsOcurrentlia	Equal variances assumed	3.223	.074	-1.391	220	.166
bilities2011	Equal variances not assumed			-3.134	204.647	.002
currentassetsOcurrentlia	Equal variances assumed	9.065	.003	-3.631	220	.000
bilities2012	Equal variances not assumed			-7.337	206.442	.000
avercurrentassetsOcurre	Equal variances assumed	4.456	.036	-1.931	220	.055
ntliabilities	Equal variances not assumed			-4.303	210.235	.000
currentliabilitiesOtotaleq	Equal variances assumed	59.636	.000	4.524	220	.000
uity2011	Equal variances not assumed			1.952	34.036	.059
currentliabilitiesOtotaleq	Equal variances assumed	21.609	.000	-1.735	220	.084
uity2012	Equal variances not assumed			-.744	34.003	.462
avercurrentliabOtotalequ	Equal variances assumed	18.318	.000	-.573	220	.567
ity	Equal variances not assumed			-.246	34.009	.807
totalliabilitiesOtotalasset	Equal variances assumed	7.719	.006	6.697	220	.000
s2011	Equal variances not assumed			5.202	40.209	.000
totalliabilitiesOtotalasset	Equal variances assumed	18.560	.000	7.651	220	.000
s2012	Equal variances not assumed			5.236	38.051	.000
avertotalliabilitiesOtotala	Equal variances assumed	12.902	.000	7.398	220	.000
ssets	Equal variances not assumed			5.364	38.947	.000
totalequityOtotalassets2	Equal variances assumed	7.850	.006	-6.721	220	.000
011	Equal variances not assumed			-5.216	40.190	.000
totalequityOtotalassets2	Equal variances assumed	18.686	.000	-7.672	220	.000
012	Equal variances not assumed			-5.247	38.041	.000
avertotalequityOtotalass	Equal variances assumed	13.042	.000	-7.421	220	.000

ets	Equal variances not assumed			-5.376	38.932	.000
salesOcurrentassets201	Equal variances assumed	8.017	.005	2.288	220	.023
1	Equal variances not assumed			1.714	39.512	.094
salesOcurrentassets201	Equal variances assumed	22.260	.000	2.592	220	.010
2	Equal variances not assumed			1.114	34.017	.273
aversalesOcurrentasset	Equal variances assumed	21.343	.000	2.689	220	.008
s	Equal variances not assumed			1.160	34.037	.254
netincomeOsales2011	Equal variances assumed	5.951	.016	-2.550	220	.011
	Equal variances not assumed			-1.360	35.363	.182
netincomeOsales2012	Equal variances assumed	28.660	.000	-4.052	220	.000
	Equal variances not assumed			-1.779	34.124	.084
avernetincomeOsales	Equal variances assumed	23.293	.000	-4.255	220	.000
	Equal variances not assumed			-1.968	34.404	.057
currentliabOtotalliab201	Equal variances assumed	.948	.331	-1.732	220	.085
1	Equal variances not assumed			-1.806	49.498	.077
currentliabOtotalliab201	Equal variances assumed	.592	.442	-.583	220	.561
2	Equal variances not assumed			-.598	48.745	.553
avercurrentliabOtotalliab	Equal variances assumed	.179	.672	-1.259	220	.209
ilities	Equal variances not assumed			-1.274	48.131	.209
receivablesOtotalassets	Equal variances assumed	5.255	.023	.630	220	.530
2011	Equal variances not assumed			.532	42.114	.597
receivablesOtotalassets	Equal variances assumed	.824	.365	-.409	220	.683
2012	Equal variances not assumed			-.372	44.161	.712
averreceivablesOtotalas	Equal variances assumed	2.102	.148	.092	220	.927
sets	Equal variances not assumed			.080	42.710	.937
salesOtotalliabilities2011	Equal variances assumed	5.861	.016	-1.634	220	.104
	Equal variances not assumed			-3.696	202.202	.000
salesOtotalliabilities2012	Equal variances assumed	4.518	.035	-1.903	220	.058
	Equal variances not assumed			-3.857	207.786	.000
aversalesOtotalliabilities	Equal variances assumed	6.637	.011	-1.922	220	.056
	Equal variances not assumed			-4.209	216.625	.000
workingcapOtotalassets	Equal variances assumed	2.205	.139	-3.604	220	.000
2011	Equal variances not assumed			-3.139	42.902	.003
workingcapOtotalassets	Equal variances assumed	2.682	.103	-5.801	220	.000
2012	Equal variances not assumed			-4.985	42.538	.000
averworkingcapitalOtotal	Equal variances assumed	1.396	.239	-4.798	220	.000
assets	Equal variances not assumed			-4.218	43.159	.000
retainedearningsOtotass	Equal variances assumed	.016	.899	-.512	220	.609
ets2011	Equal variances not assumed			-.544	50.474	.589
retainedearningsOtotass	Equal variances assumed	.322	.571	-1.146	220	.253

ets2012	Equal variances not assumed			-1.356	57.111	.180
averREOtotalassets	Equal variances assumed	.397	.529	-.863	220	.389
	Equal variances not assumed			-.978	54.138	.332
EBITOtotassets2011	Equal variances assumed	.082	.775	-.667	220	.506
	Equal variances not assumed			-1.362	210.877	.175
EBITOtotassets2012	Equal variances assumed	11.403	.001	-2.157	220	.032
	Equal variances not assumed			-1.587	39.192	.121
averEBITOtotalassets	Equal variances assumed	.036	.850	-1.067	220	.287
	Equal variances not assumed			-1.689	99.869	.094
BVofequityOBVofliabilities2011	Equal variances assumed	1.848	.175	-.814	220	.417
	Equal variances not assumed			-1.884	186.227	.061
BVofequityOBVofliabilities2012	Equal variances assumed	.743	.390	-.554	220	.580
	Equal variances not assumed			-1.282	186.197	.202
averBVequityOBVLiabilities	Equal variances assumed	1.349	.247	-.722	220	.471
	Equal variances not assumed			-1.672	186.213	.096
salesOtotalassets2011	Equal variances assumed	2.052	.153	-1.307	220	.193
	Equal variances not assumed			-1.976	88.773	.051
salesOtotalassets2012	Equal variances assumed	.635	.426	-1.124	220	.262
	Equal variances not assumed			-1.526	70.801	.131
aversalesOtotalassets	Equal variances assumed	1.239	.267	-1.228	220	.221
	Equal variances not assumed			-1.790	81.591	.077

Logistic Regression Model:

The third procedure consists of developing a logistic regression model fir each year under study, made of jointly significant ratios that can accurately predict the state of SMEs in Lebanon. The binary logistic regression is used on SPSS 20 and checked on E-views 8. The significance of the models, the meaning of the ratios, and the accuracy levels will be discussed, in addition to the interaction with the dummy variable (audited and non-audited financials) and the type of the SME (manufacturing or non-manufacturing).

Logistic Regression for the year 2011:

For the year 2011, two ratios were proved to be jointly significant book value of equity/book value of liabilities, and working capital/assets:

(Table 20)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BVeqOBVliab1	.320	.107	8.896	1	.003	1.377
	workcapOast1	2.256	.882	6.549	1	.010	9.549
	Constant	.310	.306	1.026	1	.311	1.363

a. Variable(s) entered on step 1: BVeqOBVliab1, workcapOast1.

The model deducted is the following: Y= 0.31 + exp 0.32 (Equity/Liabilities) +exp 2.256 (Working capital/Assets)

Interpretation:

Y: odds that the company will be solvent.

Equity/Liabilities: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 0.32, being 1.377. In other words, when Equity/Liabilities increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to 1.377:1. This means that the higher the equity of an SME is relatively to its debts, the higher the odds that it will be in good financial health.

Working Capital/Assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 2.256, being 9.549. In other words, when Working Capital/Assets increases by 1 unit, the odds that the SME will be solvent increases from 1:1 to 9.549:1. This indicates that the higher the working capital is relatively to assets, the better off the SME will be (working capital being current assets – current liabilities).

(Table 21)

Classification Table[a]

	Observed		Predicted		
			state		Percentage Correct
			.00	1.00	
Step 1	state	.00	3	32	8.6
		1.00	1	186	99.5
	Overall Percentage				85.1

a. The cut value is .500

(Table 22)

Prediction

Actual

	Bankrupt	Non-bankrupt	Total
Bankrupt	8.6% (no error)	91.4% (type II)	100%
Non-bankrupt	99.5% (type I)	0.5% (no error)	100%

<u>Results:</u>

3 bankrupt companies of the total 35 bankrupt companies are accurately classified as bankrupt (8.6%).

The remaining 32 are misclassified as solvent (this is the type II error, being 91.4%).

186 solvent companies of the total of 187 solvent companies are accurately classified as solvent (99.5%)

The remaining SME is misclassified as bankrupt (this is the type I error, being 0.5%).

The overall accuracy percentage is 85.1%. Formula: (8.6*35+99.5*187)/222

R^2: 0.238: this signifies that 23.8% of the variation in the dependent variable is explained by the variation in the independent variable.

Interaction with dummy variable and type:

(Table 23)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BVeqOBVliab1	.478	.179	7.096	1	.008	1.613
	workcapOast1	2.223	1.354	2.693	1	.101	9.233
	eqOliab*dummy1	-.249	.184	1.832	1	.176	.780
	workcapOast*dummy1	-.004	1.687	.000	1	.998	.996
	Constant	.261	.313	.695	1	.404	1.298

a. Variable(s) entered on step 1: BVeqOBVliab1, workcapOast1, eqOliab*dummy1,workcapOast*dummy1

As illustrated in the above table, the dummy variables are not significant in the model, meaning that the factor of the financial being audited or non-audited does not affect the predictive ability of the model. The same can be said regarding the type of the company: in fact, whether the company belongs to the manufacturing sector or non-manufacturing sector is not significant in the model. This is shown in the table below:

(Table 24)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BVeqOBVliab1	.282	.105	7.199	1	.007	1.326
	workcapOast1	2.144	.951	5.080	1	.024	8.535
	workcapOast*type1	-.040	2.212	.000	1	.986	.961
	eqOliab*type1	.417	.345	1.465	1	.226	1.517
	Constant	.257	.310	.688	1	.407	1.293

a. Variable(s) entered on step 1: BVeqOBVliab1, workcapOast1, workcapOast*type1, eqOliab*type1.

Logistic regression for the year 2012:

The ratios that proved to be jointly significant in 2012 were the following: current assets/total assets, current liabilities/total liabilities, Equity/Assets, fixed assets/total assets, log of total assets, net income/sales and receivables/total assets.

(Table 25)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	curastOtotast2	-8.702	4.133	4.432	1	.035	.000
	curliabOtotliab2	-2.513	1.029	5.962	1	.015	.081
	eqOast2	6.487	1.229	27.835	1	.000	656.279
	fixastOtotast2	-13.991	4.358	10.308	1	.001	.000
	logtotast2	.796	.300	7.049	1	.008	2.217
	netincOsales2	6.510	2.246	8.400	1	.004	672.000
	receivOtotast2	-4.528	2.007	5.091	1	.024	.011

a. Variable(s) entered on step 1: curastOtotast2, curliabOtotliab2, eqOast2, fixastOtotast2, logtotast2, netincOsales2, receivOtotast2.

Y= exp -8.702 (current assets/total assets) + exp -2.513 (current liabilities/total liabilities) + exp 6.487 (equity/assets) + exp -13.991 (fixed assets/total assets) + exp 0.796 (log of total assets) + exp 6.519 (net income/sales) + exp -4.528 (receivables/total assets)

Current assets/total assets: an increase of this ratio by 1 unit decreases the odds that the company will be solvent by the exponential of -8.702, being 0. In other words, when current assets/total assets increases by 1 unit, the odds that the SME will take the value of 1 and be solvent decreases from 1:1 to 0:1. This negative relationship indicates that the higher the current assets portion of the total assets, the more prone the company is to be subject to non-performing loans. Taking into consideration that current assets are mostly constituted of trade debtors and stock, this relationship makes sense, stating that when the company has a relatively high level of receivables and stock (assets that are not cashed in yet) it may face financial difficulties. High levels of stock may indicate slow rotation and inability to liquidate stock, and high level of trade debtors may indicate problem in collection.

Current liabilities/Total liabilities: an increase of this ratio by 1 unit decreases the odds that the company will be solvent by the exponential of -2.513, being 0.081. In other words, when this ratio increases by 1 unit, the odds that the SME be solvent decreases from 1:1 to 0.081: 1. The higher this ratio is the more prone to financial difficulties the SME will be. The current liabilities are mostly made of trade creditors and loan amounts that mature in less than 1 year. In fact, when current liabilities are high compared to total liabilities, the company has a lot of dues to pay during less than 1 year. So the higher the amount of short term debt, the more likely the SME will face financial difficulties.

Equity/Assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 6.487, being 656.28. In other words, when this ratio increases by 1 unit, the odds that the SME be solvent increases from 1:1 to 656.28: 1. This signifies that the higher the equity portion of assets (in contrast with portion of liabilities from assets), the lower the risk of facing financial difficulties, indicating that an SME is better off when it relies on equity financing rather than debt financing.

Fixed assets/Total assets: an increase of this ratio by 1 unit decreases the odds that the company will be solvent by the exponential of -13.991, being 0. In other words, when Fixed assets/Total assets increases by 1 unit, the odds that the SME will take the value of 1 and be solvent decreases from 1:1 to 0:1. A high the portion of fixed assets of total assets indicates a low portion of current assets from total assets. Thus, this negative relationship means that for a company to be in good shape, it must have a good portion of its assets that can be easily liquidated.

Log of total assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 0.796, being 2.217. In other words, when the log of total assets increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to 2.217:1. This indicates that the bigger an SME is in terms of overall assets, the more prone to solvency and performing loans it will be.

Net income/Sales: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 6.51, being 672. In other words, when Net income/Sales increases by 1 unit, the odds that the SME will be solvent increases to 672:1. This signifies that the higher the profitability, the lower the risk of facing financial difficulties.

Receivables/Total assets: an increase of this ratio by 1 unit decreases the odds that the company will be solvent by the exponential of -4.528, being 0.011. In other words, when this ratio increases by 1 unit, the odds that the SME will be solvent decreases from 1:1 to 0.011:1. This signifies that the higher the receivables portion of assets, the higher the risk of facing financial difficulties. Since receivables are assets that are not cashed in yet, their high level may indicate doubtful accounts and problems in collection.

(Table 26)

Classification Table[a]

	Observed		Predicted		
			state		Percentage Correct
			.00	1.00	
Step 1	state	.00	18	17	51.4
		1.00	4	183	97.9
	Overall Percentage				90.5

a. The cut value is .500

(Table 27)

Prediction

Actual

	Bankrupt	Non-bankrupt	Total
Bankrupt	51.4% (no error)	48.6% (type II)	100%
Non-bankrupt	2.1% (type I)	97.9% (no error)	100%

Results:

18 bankrupt companies of the total 35 bankrupt companies are accurately classified as bankrupt (51.4%).

The remaining 17 are misclassified as solvent (this is the type II error, being 48.6%).

183 solvent companies of the total of 187 solvent companies are accurately classified as solvent (97.9%)

The remaining 4 are misclassified as bankrupt (this is the type I error, being 2.1%).

The overall accuracy percentage is 90.5%. Formula: (51.4*35+97.9*187)/222.

R^2: 0.779: this signifies that 77.9% of the variation in the dependent variable is explained by the variation in the independent variable.

Interaction with dummy variable and type:

To test the significance of the financials being audited or non-audited, the interaction between each of the variables in the above model and the dummy variable is calculated, and the relative p-value is extracted. As the below table shows, none of the interaction has a p-value lower than 0.05, meaning that the dummy variables is not significant, and whether the financials are audited or not does not make a difference in the prediction of the state of the SME.

(Table 28)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	curastOtotast2	659.347	452.347	2.125	1	.145	2.242E+286
	curliabOtotliab2	-.634	1.609	.155	1	.694	.530
	eqOast2	5.819	1.803	10.421	1	.001	336.753
	fixastOtotast2	654.645	452.459	2.093	1	.148	2.036E+284
	logtotast2	.811	.399	4.136	1	.042	2.251
	netincOsales2	7.046	3.278	4.621	1	.032	1147.807
	receivOtotast2	-5.334	2.551	4.372	1	.037	.005
	curastOtotastdummy2	1.463	8.896	.027	1	.869	4.319
	curliabOtotliabdummy2	-3.205	2.273	1.988	1	.159	.041
	eqOastdummy2	.910	2.620	.121	1	.728	2.484
	fixastOtotastdummy2	1.128	9.291	.015	1	.903	3.090
	logtotastdummy2	.001	.643	.000	1	.998	1.001
	netincOsalesdummy2	-1.905	4.807	.157	1	.692	.149
	receivOtotastdummy2	1.287	4.243	.092	1	.762	3.622
	Constant	-669.080	453.541	2.176	1	.140	.000

a. Variable(s) entered on step 1: curastOtotast2, curliabOtotliab2, eqOast2, fixastOtotast2, logtotast2, netincOsales2, receivOtotast2, curastOtotastdummy2, curliabOtotliabdummy2, eqOastdummy2, fixastOtotastdummy2, logtotastdummy2, netincOsalesdummy2, receivOtotastdummy2.

The interaction of each variable in the model is also tested with the type of the company (manufacturing or non- manufacturing), and as per the below table, the p-values of the interactions are all above 0.05, meaning that the company's type is not a significant predictor of its state.

(Table 29)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	curastOtotast2	299.688	474.818	.398	1	.528	1.422E+130
	curliabOtotliab2	-1.942	1.114	3.042	1	.081	.143
	eqOast2	6.190	1.356	20.828	1	.000	487.885
	fixastOtotast2	294.611	474.961	.385	1	.535	8.869E+127
	logtotast2	.670	.303	4.900	1	.027	1.954
	netincOsales2	4.798	2.272	4.461	1	.035	121.266
	receivOtotast2	-4.982	2.039	5.972	1	.015	.007
	curastOtotasttype2	-72.555	55.452	1.712	1	.191	.000
	curliabOtotliabtype2	-2.305	5.087	.205	1	.650	.100
	eqOasttype2	7.887	9.027	.763	1	.382	2661.361
	fixastOtotasttype2	-79.263	61.891	1.640	1	.200	.000
	logtotasttype2	5.172	3.938	1.724	1	.189	176.201
	netincOsalestype2	33.618	31.887	1.111	1	.292	398077906556943.800
	receivOtotasttype2	2.563	10.683	.058	1	.810	12.974
	Constant	-306.907	475.279	.417	1	.518	.000

a. Variable(s) entered on step 1: curastOtotast2, curliabOtotliab2, eqOast2, fixastOtotast2, logtotast2, netincOsales2, receivOtotast2, curastOtotasttype2, curliabOtotliabtype2, eqOasttype2, fixastOtotasttype2, logtotasttype2, netincOsalestype2, receivOtotasttype2.

Logistic Regression for the average of the years 2011 and 2012:

The ratios that proved to be jointly significant in the average of the years 2011 and 2012 were the following: Equity/Assets, Working capital/Assets, Net income/Sales, Sales/Assets, Log of total assets, Receivables/Total assets, Net income/Fixed assets.

(Table 30)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	avereqOast	3.776	1.089	12.019	1	.001	43.648
	averworkcapOast	4.760	1.409	11.410	1	.001	116.795
	avernetincOsales	5.866	2.265	6.707	1	.010	352.973
	aversalesOast	.628	.329	3.648	1	.056	1.874
	averlogtotast	.647	.244	7.010	1	.008	1.910
	averreceivOtotast	-3.550	2.408	2.173	1	.140	.029
	avernetincOfixast	-.020	.013	2.609	1	.106	.980
	Constant	-11.450	3.600	10.118	1	.001	.000

a. Variable(s) entered on step 1: avereqOast, averworkcapOast, avernetincOsales, aversalesOast, averlogtotast, averreceivOtotast, avernetincOfixast.

Y= -11.45 + exp 3.776 (Equity/Assets) + exp 4.76 (Working capital/Assets) + exp 5.866 (Net income/Sales) + exp 0.628 (Sales/Assets) + exp 0.647 (Log of total assets) + exp -3.55 (Receivables/Total assets) + exp -0.02 (Net income/Fixed assets).

Equity/Assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 3.776, being 43.648. In other words, when this ratio increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to 43.648:1. This signifies that the higher the equity relatively assets (in contrast with the size of liabilities relative to assets), the lower the risk of facing financial difficulties. This indicates that a company is more prone to solvency when its own funds (capital, retained earnings, annual profit) are higher than its debts.

Working capital/Assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 4.76, being 116.795. In other words, when the log of total assets increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to almost 117:1. This signifies that the higher the working capital amount, the higher the lower the risk of facing financial difficulties. A high working capital a great difference between current assets and current liabilities (current assets exceeding current liabilities).

Net income/Sales: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 5.866, being 352.973. In other words, when this ratio increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to almost 353:1. This signifies that the higher the profitability, the better the financial situation the company will be in and the lower the risk of facing financial difficulties.

Sales/Assets: an increase of this ratio by 1 unit increases the odds that the company will be solvent by the exponential of 0.628, being 1.874. In other words, when this ratio increases by

1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to 1.874:1. This signifies that the higher the sales relative to assets, the lower the risk of facing financial difficulties. This indicates that sales must be high enough to cover a significant part of the assets value.

Log of total assets: an increase of this indicator by 1 unit increases the odds that the company will be solvent by the exponential of 0.647, being 1.91. In other words, when this ratio increases by 1 unit, the odds that the SME will take the value of 1 and be solvent increases from 1:1 to 1.91:1. This signifies that the higher the assets amount, the lower the risk of facing financial difficulties.

Receivables/Total assets: an increase of this indicator by 1 unit decreases the odds that the company will be solvent by the exponential of -3.55, being 0..29. In other words, when this ratio increases by 1 unit, the odds that the SME will take the value of 1 and be solvent decreases from 1:1 to 0.029:1. This signifies that the higher the receivables portion of assets, the higher the risk of facing financial difficulties. Since receivables are payments not yet cashed by customers, their high level may indicate problem in collection, thus a company with very high receivables may face a squeeze of liquidity and have financial difficulties.

Net income/Fixed assets: an increase of this indicator by 1 unit decreases the odds that the company will be solvent by the exponential of -0.02, being 0.98. In other words, when this ratio increases by 1 unit, the odds that the SME will take the value of 1 and be solvent decreases from 1:1 to 0.98:1. This signifies that the higher the net profit relative to fixed assets (or lower the fixed assets compared to net income), the higher the risk of facing financial difficulties. In a healthy company, fixed assets (which can be made of the business premises, the machines and equipment…) are normally at a high level, indicating that the company owns the premises or the equipment and therefore save additional expenses such as their relative rent or lease…

(Table 31)

Classification Table[a]

	Observed		Predicted		
			state		Percentage Correct
			.00	1.00	
Step 1	state	.00	16	19	45.7
		1.00	6	181	96.8
	Overall Percentage				88.7

a. The cut value is .500

(Table 32)

Prediction

Actual

	Bankrupt	Non-bankrupt	Total
Bankrupt	45.7% (no error)	54.3% (type II)	100%
Non-bankrupt	3.2% (type I)	96.8% (no error)	100%

Results:

16 bankrupt companies of the total 35 bankrupt companies are accurately classified as bankrupt (45.7%).

The remaining 19 are misclassified as solvent (this is the type II error, being 54.3%).

181 solvent companies of the total of 187 solvent companies are accurately classified as solvent (96.8%)

The remaining 6 are misclassified as bankrupt (this is the type I error, being 3.2%).

The overall accuracy percentage is 88.7%. Formula: (45.7*35+96.8*187)/222.

R^2: 0.508 this signifies that 50.8% of the variation in the dependent variable is explained by the variation in the independent variable.

Interaction with dummy variable and type:

The significance of the dummy variable is tested again, and the below results show that it is not significant.

(Table 33)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	avereqOast	4.966	1.825	7.403	1	.007	143.492
	averworkcapOast	3.040	2.555	1.416	1	.234	20.912
	avernetincOsales	8.050	4.324	3.466	1	.063	3133.864
	aversalesOast	1.173	.974	1.449	1	.229	3.231
	averlogtotast	1.610	.473	11.589	1	.001	5.004
	averreceivOtotast	-9.780	4.388	4.967	1	.026	.000
	avernetincOfixast	2.920	3.061	.910	1	.340	18.546
	eqOastdummyaver	-1.740	2.429	.513	1	.474	.176
	workcapOastdummyaver	3.629	3.455	1.104	1	.293	37.680
	netincOsalesdummyaver	-.681	5.404	.016	1	.900	.506
	salesOastdummyaver	-.413	1.033	.160	1	.689	.662
	logtotastdummyaver	.072	.137	.273	1	.601	1.074
	receivOtotastdummyaver	5.533	5.350	1.070	1	.301	252.982
	netincOfixastdummyaver	-2.948	3.061	.928	1	.335	.052
	Constant	-25.986	7.038	13.631	1	.000	.000

a. Variable(s) entered on step 1: avereqOast, averworkcapOast, avernetincOsales, aversalesOast, averlogtotast, averreceivOtotast, avernetincOfixast, eqOastdummyaver, workcapOastdummyaver, netincOsalesdummyaver, salesOastdummyaver, logtotastdummyaver, receivOtotastdummyaver, netincOfixastdummyaver.

The significance of the type is also tested. As per the below table, the type proved to have no significant effect on the prediction of the financial state of a company.

(Table 34)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	avereqOast	3.321	1.382	5.771	1	.016	27.682
	averworkcapOast	5.156	1.668	9.556	1	.002	173.425
	avernetincOsales	6.909	2.737	6.370	1	.012	1001.017
	aversalesOast	1.092	.408	7.166	1	.007	2.981
	averlogtotast	1.335	.402	11.034	1	.001	3.799
	averreceivOtotast	-6.091	2.963	4.226	1	.040	.002
	avernetincOfixast	-.018	.014	1.646	1	.200	.982
	eqOasttypeaver	.161	3.308	.002	1	.961	1.174
	workcapOasttypeaver	-.055	4.498	.000	1	.990	.947
	netincOsalestypeaver	4.942	8.466	.341	1	.559	140.054
	salesOasttypeaver	-1.822	1.440	1.600	1	.206	.162
	logtotasttypeaver	.099	.168	.350	1	.554	1.105
	receivOasttypeaver	5.875	7.383	.633	1	.426	355.921
	netincOfixasttypeaver	1.414	1.717	.678	1	.410	4.112
	Constant	-21.432	5.748	13.904	1	.000	.000

a. Variable(s) entered on step 1: avereqOast, averworkcapOast, avernetincOsales, aversalesOast, averlogtotast, averreceivOtotast, avernetincOfixast, eqOasttypeaver, workcapOasttypeaver, netincOsalestypeaver, salesOasttypeaver, logtotasttypeaver, receivOasttypeaver, netincOfixasttypeaver.

CHAPTER FIVE
SUMMARY OF FINDINGS AND RECOMMENDATIONS

5.1 Findings

As stated through the research questions, this study mainly aimed to test the applicability of the Altman Z scores on the SMEs in Lebanon, to identify which financial ratios are the best predictors of the financial states of subject companies, and to develop a model that can predict the state of a company.

<u>Finding 1:</u> the Altman Z-score models are not applicable on SMEs in Lebanon

The application of the Altman Z'score and Z" score on SMEs in Lebanon showed modest percentage of accuracy in prediction of bankrupt SMEs as bankrupt despite high accuracy in classifying actually solvent SMEs as solvent, since the type II error (being the main focus of our study and the most important category) was relatively high in all cases. The type II error ranged between 31.4% and 57.1% when the Altman models were applied on the SMEs regardless of their type (manufacturing/non-manufacturing), while it ranged between 28.6% and 57.1% when the models were applied based on the type of each SME. Accordingly, the models' accuracy percentage in the classification of bankrupt companies as bankrupt were relatively low, which ranged between 25.7% amd 40% when the Altman models were applied regardless of the SME type, and between 0% and 35.7% when applied according to

SME type. As for the solvent SMEs, the Altman models were able to accurately classify 67.4% to 94.1% of the sample when applied regardless of type, and 60.7% to 95.4% when applied according to SME type. This resulted in a relatively low type I error.

Finding 2: some of an SME's financial ratios are individually significant

The financial ratios that proved to be significant during 2011, 2012 and the average of both years are the following: liabilities/assets, liquid assets/current assets, sales/liabilities and working capital/assets. Other variables proved to be significant in one year and/or the average, however the variables which are significant during all the years under study are considered more significant.

Finding 3: the logistic regression models are not applicable on SMEs in Lebanon

The logistic regression models did not result in high accuracy levels in the prediction of bankrupt companies as being bankrupt, resulting in high type II error. However, the models did achieve high accuracy levels in the prediction of solvent companies as being solvent. The model that achieved the best results in the 2012 model, which was able to classify 97,9% of the actually solvent companies as solvent, leading to a to a type I error of 2.1%. However, this model accurately classified only 51.4% of the bankrupt companies as bankrupt, resulting in a high type II error of 48.6%.

<u>Finding 4:</u> the ratios that proved to be jointly significant in developed the logistic regression models are different from the variables which constitute the Altman z-score models.

In the year 2011, two ratios (Book value of equity/ Book Value of liabilities) constituted the logistic regression model and were both part of the Altman models. In the year 2012, the developed model included none of the Altman models components. For the average of the years 2011 and 2012, the developed logistic model which constituted seven variables, included two of the Altman models components, being the Working capital/Assets and the Sales/Assets.

<u>Finding 5:</u> whether the financial statements of an SME are audited or not audited did not affect the predictive ability of a model.

This is evidenced by the high p-values registered by the interaction between the variables in the models and the dummy variable during all the years under study.

<u>Finding 6:</u> the type of an SME (manufacturing or non-manufacturing) did not affect the predictive ability of a model.

This is evidenced by the high p-values registered by the interaction between the variables in the models and the type of the SMEs during all the years under study.

5.2 Conclusion

From the above study and findings, we can conclude that it is difficult to predict bankruptcy in Lebanon using only quantitative data (being financial ratios).

Although the Altman models and the developed logistic regression models attained high accuracy levels in predicting the healthy state of solvent companies, they failed to achieve high accuracy results in the prediction of the bankrupt state of financially unhealthy companies, which is the aim of credit risk management, thus, it can be concluded that models using only quantitative data cannot predict which SMEs will be subject to non-performing loans in Lebanon. A more comprehensive view of the business through taking into consideration qualitative data concerning the management of the company, the succession preparation, the banking history, the legal history can yield to a better analysis, assessment and prediction of a company's financial state.

Another conclusion is that some financial ratios are worth focusing on when assessing a company's financial health, since they significantly differ between a solvent company and a bankrupt company. The Liabilities/Assets ratio is lower for solvent companies, in fact the average of this ratio for the solvent companies was around 0.28, while it reached 0.58 for bankrupt companies. For liquid assets/current assets, it is lower for a solvent company compared to a bankrupt company, reaching an average 0.45 for the former and 0.57 for the latter. As for Sales/Liabilities, it is higher for solvent companies than bankrupt companies, evidenced by the average of 12.16 for healthy companies and 2.79 unhealthy companies. The Working capital/Assets ratio is higher for a solvent company than for a bankrupt company, where the average for the former is 0.27 and 0.06 for the latter.

The Altman Z scores were found to be inapplicable in Lebanon due to the low accuracy levels registered in the prediction of the financial health of SMEs in Lebanon, although based on the literature review, they achieved moderate to high accuracy levels in various countries. This can be explained by the differences in the cultural and economic settings in each country, and also the quality of the financial statements studied. These factors could also be linked to the finding that states that the logistic regression models used financial ratios other than the ones used by Altman in his models.

Furthermore, another explanation for why the Altman Z scores and also the logistic regression models could not achieve high accuracy results is linked to the idea of market efficiency. The concept of market efficiency was developed in 1970 by Economist Eugene Fama whose theory stated that it is not possible for an investor to outperform the market because all available information is already built into all stock prices. Thus, in an efficient market, financial variables and situations cannot be predicted. Someone who could predict future financial states would make millions by trading on the information. Therefore it is expected that the first and third tests will be highly inaccurate considering that there aim is to predict solvency while the second test will be more accurate since it focuses of significant differences between health and unhealthy companies.

Concerning the result generated stating that whether the financial statements of a company are audited or non-audited does not affect the outcome of the bankruptcy prediction model, an explanation would be that in Lebanon, both types of financial statements reflect the reality of the SME, and audited statements are not significantly different than non-audited statements; minor differences can exist but they are not significant enough to affect the results. Another explanation would be that there is a significant difference between the types of statements, but because the percentage of audited statements (43%) is a bit lower than the percentage of non-audited statements (57%), the outcome of the models was not affected. A study to further investigate this matter should be conducted.

In summary, in order to have a good assessment of a client, many factors must be taken into consideration. When analyzing the financials, the ratios stated above should be considered, after a global view of the balance sheet, income statement and cash flow statement. The business as a whole should be viewed in an objective manner, considering the macroeconomic conditions in the region, such as the economy of the country, the political situation, the settings of the industry to which the business belongs to…

5.3 Recommendations

Based on the findings of my study, it is not recommended to apply the Altman Z-score models on SMEs in Lebanon.

In addition, some financial ratios with predictive ability are worth focusing on during the analysis of the financial health of a company which are liabilities/assets, liquid assets/current assets, sales/liabilities and working capital/assets.

Finally, since the models using only quantitative variables did not result in high accuracy levels, further research conducted using qualitative variables such as years of experience of the SME in the market, geographical location, history of repayment in the bank, financial literacy of the business owners, the economical state of the region or the country … could add to the predictive ability of the logistic regression model. Also, a larger sample especially for bankrupt firms would provide more significant results. Moreover, taking financial statements of companies for longer periods of time (i.e. 5 years prior to bankruptcy instead of two years prior to bankruptcy) may help generate more robust models.

5.4 Limitations

I focused my dissertation on SMEs in Lebanon, provided by one Alfa bank in Lebanon. Due to the strict banking secrecy laws in Lebanon, I was not able to acquire the financials of corporate companies from that bank, neither other financial statements of SMEs or corporate companies from other banks. The sample size is rather small and more reliable results would have been achieved by the logistic regression models with a greater sample, especially with a larger number of firms in distress.

In addition, some components were missing from the financial statements of the SMEs understudy, making some financial ratios inapplicable.

Finally, I was capable of gathering financial statements for the SMEs under study for only two years prior to bankruptcy, due to the limited data sources.

APPENDIX

The Models

Altman Z'-score: $Z' = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5$

- X1= Working Capital/Total Assets
- X2 = Retained Earnings/Total Assets
- X3= Earnings Before Interest and Taxes/Total Assets
- X4 = Book Value of Equity/Book Value of Total Liabilities
- X5 = Sales/Total assets

The score values are interpreted as follows:

>2.90 = Tend not to fail

1.23-2.90 = Grey area

<1.23 = Tend to fail

Altman Z"-score: $Z'' = 6.56 X1 + 3.26 X2 + 6.72 X3 + 1.05 X4$

X 1: Working Capital/Total Assets;

X2: Retained Earnings/Total Assets;

X3: Earnings Before Interest and Taxes/Total Assets;

X4: Book Value of Equity/Book Value of Total Liabilities;

The score values are interpreted as follows:

>2.90 = Tend not to fail

1.23-2.90 = Grey area

<1.23 = Tend to fail

The Financial Ratios and Indicators Selected

Net Income/ Equity

Liabilities/ Equity

Equity/ Fixed Assets

Current Assets/ Total Assets

Net Income/ Fixed Assets

Liquid Assets/ Current Assets

Source: Kovács, Dóczi, Erdély, Falfalusi, Knoch & Patka, 2011.

Additional ratios from Altman Z-score models:

- Working Capital/Total Assets
- Retained Earnings/Total Assets
- Earnings Before Interest and Taxes/Total Assets
- Book Value of Equity/Book Value of Total Liabilities
- Sales/Total assets

Current Assets/Current Liabilities,

Current Liability/Total Equity

Total Liabilities /Total Assets

Total Equity/Total Asset

Sales/Current Assets

Net Income/Sales

Source: Sirirattanaphokun and Pattarathammas, 2012.

Log of total assets

Source: Onofrei, 2014.

Current liabilities / total liabilities

Receivables / total assets

Fixed assets / total assets

Sales / total liabilities

Source: Waszkowski, 2011.

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