AMERICAN UNIVERSITY OF BEIRUT

THE DETERMINANTS OF LOAN DEFAULT RISKS AMONG SMALL AND MEDIUM AGRO-FOOD ENTERPRISES IN LEBANON

by
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AN ABSTRACT OF THE THESIS OF

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This paper investigates the determinants of loan repayment default among Small and Medium Agro-Food Enterprises (SMEs) in Lebanon. Data used in this study was retrieved from KAFALAT S.A.L. a Lebanese financial institution that assists SMEs to access bank financing by providing loan guarantees. The study employ the Logistic Regression model to investigate factors that influence borrower's loan repayment default. The results showed that loan period, regions, legal structure and guarantee program affect significantly the likelihood of loan repayment default. Longer repayment periods are more likely to increase loan repayment default for all five sectors examined. However, guaranteed loans under the "Basic guarantee program (75%)" are less likely to default than other programs. These results lay the foundation for a credit-scoring model, which could decrease KAFALAT's underwriting costs while maintaining their social mission. Credit scoring models help financial institutions quantify their risks, which often allows them to extend more credit in the small to medium Agro-food business community.

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CHAPTER I

INTRODUCTION

A. Background

The Small and Medium Enterprises (SMEs) constitute an important component of the economy of any country (Aranoff et al. 2010). They are the starting point of every entrepreneurial initiative (Abor & Quartey 2010). Following the evolution curves that depend on many factors, an SME has the potential to become a large company with hundreds of employees while generating big revenues (Schaper 2002). It can transform from a private entity to a public company whose shares can be listed in the financial markets (Zoltan Acs 2006). SMEs constitute the majority of firms operating in their respective countries. According to Zoltan, as a general observation, SMEs still find difficulties in their access to finance.Given their simple structures compared to big companies (administratively, operationally and financially) and their short life cycle on average, Schaper claims that SMEs do not have the same financing opportunities as large companies. The traditional credit culture, adopted by the majority of commercial banks, is often based on the evaluation of the borrower's equity (Abor Joshua & Nicholas Biekpe, 2006). For this reason, some initiatives by the states or the private sectors involve the development of legislations or plans to facilitate SMEs' access to bank financing, including the SME loan guarantee programs.

In Lebanon, since the civil war, the banking sector has often been associated with the financing of public debt; banks reduced the issuance of loans to individuals to minimal levels (Vienna Initiative Working Group, 2015). In 1999, the Lebanese government approved a law on the establishment of a mechanism to subsidize interests on loans for SMEs. Moreover, they approved the founding of KAFALAT SAL, which is a the financial institution in charge of guaranteeing loans to SMEs operating in Lebanon.

B. Statement of the Problem

Since the effective inception of the KAFALAT program in 2000, the SME's loan-banking portfolios evolved in terms of lending volume and geographic scope to cover the entire Lebanese territory. The application process, analysis and loans approval to SMEs have experienced quantitative and qualitative changes. These changes allowed a better treatment by the commercial banks for all applications related to SME loans. However, the common practice in the analysis and approval of loan applications for SMEs meets the relational approach, which is based on available expert scoring systems and their own officers' experience in the specific field. Therefore, determining the borrower's quality and the loan's riskiness follows qualitative attributes (A.M. Featherstone, 2006). The final decision to grant a loan is based on two choices: Acceptance or Rejection of the application. This approach is adopted in most of the funding programs for SMEs in the world. However, it should be adjusted and revised according to real up-to-date data in order to redefine the existing ratings in the expert Scoring system, especially the qualitative attributes pertaining to the borrower, industry and geographic region. The process of approving SME loans in our Lebanese Banks does not include their own estimation of probability of default of loan repayment, neither the segmentation of the default risk.

Loan default is a key element of credit risk, especially at the individual level. It is defined as the failure of the borrower to repay his debts according to the assigned terms. Good loan applications and acceptable levels of risk are assigned by the banks based on their own expert system. This procedure is important especially with the systemic shocks that hit the heart of the banking industry in 2008 and the reforms from the new Basel II that encourage banks, within the framework of good risk management practices, to implement internal rating systems that measure the probability of default for each of their borrowers (Mason, 2009).

In the Lebanese context, the Lebanese banks use, during the SME loan approval process, a general scoring software that is usually applied to large companies. Therefore, these scorings are based on generic models that do not take into account the situation of the country. Moreover, valuation models based solely on accounting data and balance sheets are doomed to fail given the problems of financial transparency provided by SMEs in Lebanon and the lack of legislation on financial accounting. Only the existing expert systems can reflect the reality of SMEs. However, these systems need to be updated regularly.

In the context of guaranteed SMEs loans in Lebanon, the bank's premium fee and interest charge paid by the borrower for his guaranteed loan is uniform regardless of its profile, economic sector, geographical area or loan duration. Thus, the main concern of this study is to determine the default risks, by analyzing SMEs loans, to understand the link between loan repayment ability and some components of these loans. In addition, we will draw conclusions that aim to benchmark existing expert systems in the Lebanese banks and the SMEs loan guarantee program during its 15 years of activity.

The purpose of this study can be summarized as follows:

Is it possible to better determine and analyze the loan defaults from the analysis of the SMEs characteristics in Lebanon? Moreover, how can we integrate our results in the loan approval process?

In this study, we will test potential changes and allow a better understanding of the dynamics of the relationship between the loan repayment risk and some variables that will be described in details in Chapter V. Moreover, we will present a statistical analysis based on Lebanese guaranteed SMEs loans dataset.

C. Objectives of the Study

The main objective of the study is to enable Lebanese commercial banks to better calibrate their expert systems related to SME financing. The study may be a good tool for Scoring and Pricing of SME loans and should provide results that can be used in the best practice approach within SMEs guarantee loans programs.

Our study will also determine the risks facing the entrepreneurial activities, and analyze and explain certain elements of the Lebanese entrepreneur profile. Finally, we will present and evaluate the performance of the SMEs loan guarantee program in Lebanon, namely KAFALAT.

This study is divided into five chapters. The Chapter Two is a review of the literature, pertaining to SMEs, their environment, their funding and their impact on the economy. Then we will explore a number of different valuation models used in the estimation of default probabilities. Moreover, we will focus on the Lebanese context of SMEs and the historical performance of financial actors in this area, including commercial banks and the SMEs loan guarantee program, KAFALAT. The Third Chapter presents the research structure and methodology. In the fourth Chapter, we will explore our empirical results and discussions, including our sample characteristics and the description of the variables used from KAFALAT Dataset. Finally, the Fifth Chapter is a conclusion that reviews the limitations of the study and suggestions for further studies in this field.

CHAPTER II

LITERATURE REVIEW

This chapter presents a general overview of the major problems related to Small and Medium Agro-Food Enterprises. We will further cover the environment and characteristics of Small and Medium enterprises, their contribution to the economic development as well as the problems that these enterprises encounter with banks in access to finance. Moreover, we will discuss previous literature related to determinants of default and evaluation of risks of default models.

A. Small and Medium Enterprises (SMEs): General overview

1. SME Definition

There is no universal definition for Small and Medium Enterprises (SMEs). SMEs are considered as economic entities that can take various legal forms (Sole Proprietorship, Joint Stock Company, and Limited Liability Companies) (Kenney, 2014). However, the number of employees, turnover, profitability and net worth determine the size of these enterprises (Storey, 1994). While many tried to define these enterprises, the Bolton committee (1971) made the first step towards overcoming this issue. They adopted a economic and statistical explanation of SMEs. The first related to the contribution of the enterprise to the GDP, export and employment in the country, and the second to the type of busienss structure and the market share of the enterprise.

On a general level, a Small Enterprise is a firm that has a total of fixed assets less than 250,000 dollars in value (The World Bank, 1976). Moreover, according to

Grindle et al. (1989) these firms have less than or equal to 25 employees. Another definition for Small Enterprises by the United States Agency for International Development (USAID) considers that firms with less than 50 employees (1994). According to the European Union, a Medium Enterprises have employees less or equal to 250 and their annual turnover does not overpass the 50 Million Euros.

In Lebanon, the country of interest, there is no common definition that exists for SMEs. The only reference observed to SMEs is Law 24/1999, authorizing the National Deposit Guarantee Institution (NDGI) to participate in a Lebanese Joint Stock Corporation named “KAFALAT” that helps SMEs by providing loans guarantees. This latter defines a small business as an entity with less than 40 employees who are enrolled in the National Social Security Fund (NSSF). Therefore, daily workers and contract based employees are not counted. No reference is mentioned regarding the annual turnover of the firm. However, a sample examination of guaranteed loans granted by KAFALAT shows an annual turnover ranging from 50,000 USD and 3 Million USD.

2. Characteristics of SMEs

We characterize an SME by its structural, functional and financial traits that make it different from large companies (Storey, 1994). Given that the start of any small and medium business was the idea of an individual, management is focused around the owner of this business (E., 1971). Therefore, it has a flat structure, often a family business, with either no managerial levels or many hierarchical levels of management and administration (Yang, 2009). This means a close relationship between the owner and his employees resulting in a less formal connection and a simple internal information system. The external system is simple as well which is often based on direct contacts with the clients and suppliers (Bernanke, 1989). The equity of an SME is, most of the time, private (KFW Bank, 2015). In Lebanon, all SMEs' equities are private (Association of Banks In Lebanon, 2016). These funds are not large and not diversified which is the result of family self-financing. Despite of the small size of SMEs, they have an important financial structure (Federal Ministy of Economics and Technology, 2015). SMEs are different from large enterprises where they have more flexibility and ability to innovate quickly and to adapt easily to the market. Thus, they are affected rapidly to any economic shock in the country (Federal Ministy of Economics and Technology, 2015).

3. SMEs' Contribution to economic development

SMEs constitute 99.8% of operating companies in non-financial sectors of the economy of the European Union, employing more than two thirds of the labor force (67.4%) and generating 57.9% of the total annual value added (Eurostat, 2015). Moreover, SMEs contribute to most of the job creation over the long term. They strongly contribute to economic growth every time new enterprises enters the market with new effective and more promising innovations. This process has increased the growth of the American productivity by 25% between 1977 and 1987 (Foster, 1998).

In Lebanon, applying the standards imposed by the European Union, Small and Medium Enterprises account for the majority of businesses in Lebanon (between 93 and 95%) (Ministry of Economy and Trade, 2014). The Lebanese economy relies primarily on SMEs to create jobs. Lebanese SMEs benefit from a sizable labor force (Ministry of

Finance, 2013). Moreover, the Agro-industrial SMEs, to which our study is related, form a major contributor to the Lebanese economy as well. According to an IDAL report, It generates around 26.3% of the industrial sector output and around 2.2% of the country's GDP. It also accounts for 25% of the industrial sector workforce. Agro-food activities are mostly concentrated in Mount Lebanon where 34% of agro-industrial enterprises are located (Lebanese National Accounts, 2013). International organizations have launched several initiatives in support of the Lebanese agro-industrial sector.

4. General Issues with SMEs' Access to Finance

Despite the importance of SMEs and given their productive role in the economic growth and development, the issue with access to finance has always been one of their major problems affecting their competitiveness and performance. This means that some SMEs cannot obtain financing from banks to develop their ideas and grow their enterprises. Financing constraints have remained one of the most critical barriers affecting SMEs growth (Aldaba et al, 2010). Two main factors would lead to these barriers. Internal factors that are related to the structure of the enterprises and their financial statements, and the collateral available. The External factors are related to the attitude of banks towards SMEs and the miscommunication of the financial information with the Banks.

Another obstacle that limits SMEs access to finance in Lebanon is the lack of understanding of the agricultural markets and seasons affecting the enterprise's cash inflow (Chami, 2014).

5. Responses to the Issues in Access to Finance for SMEs in Lebanon

Given the important role that SMEs play in the economy, several initiatives took place to facilitate their access to finance. The one related to our study is linking SMEs to private banks, conducting feasibility studies, and making use of the loan guarantees facilitated by KAFALAT. The loan guarantees are concerned in bringing financing to SMEs through bank loans guarantee programs (LGP) (Thomas, 2000). The mechanism of these programs can be summarized as follows: The bank provides a loan to SMEs against a letter of guarantee from a LGP, covering a percentage of the loan, in case of default by the borrower, for a determined period and covering the whole period of the credit while taking a certain commission. LGP becomes the insurer of SMEs to the lending bank. This reduces the exposure risk incurred by the bank and a good credit risks expansion tool. This has helped in strengthening creditor rights and credit information sharing, by the use of the Central Bank's Risk Center. LGP can take the form of a private company like KAFALAT in Lebanon. Their main task is to motivate entrepreneurs and new projects, especially those of innovation, potential sponsors and great benefit to the society. In addition, some LGP offers, besides the bank loan guarantee, training for entrepreneurs and financial advices as they ensure the exchange of technical expertise between SMEs in the same industry through their various business networks and finance.

In summary, LGP faces many issues related to the cost of obtaining information, which is crucial to the loan approval decisions (Stiglitz, 1981). Since little information is available on SMEs, the costs of obtaining it by the lending bank are high while sharing it is free. Therefore, the bank will be demotivated to obtain more information, which implies less loans due to its low profitability. LGPs then intervene to motivate and encourage the collection and dissemination of information on SME borrowers who would not be served otherwise.

B. Loan default: Overview of risk assessment models

The importance and role of LGP in financing SMEs is considered as the loan risk cover techniques to banks. It addresses the most important part of the loan. Once granted to an SME or a large company, the identification, estimation and measurement of the credit risk is fundamental to the entire credit process. Moreover, it is important for the bank to select the less risky loans following the overall market, industry and individual financial information. The following section will carry out a general review on credit risk and the different methods used to estimate probability of default, going from the most general systems, away from the environment of SMEs, to the current practices applied to SMEs.

1. General overview of some evaluation models

Estimating default probabilities for private enterprises is the first step in the banks' credit risk analysis and assessment for potential losses. Credit risk is defined as the risk that the borrower would not repay his debt on time; an outstanding debt is economically a loss for the bank. Thus, the bank's interest is to integrate the analysis and modeling of risks into their financial management systems to minimize their losses and to comply with the profitability investment principle. The objective of a credit risk model is to estimate the probability of distribution for future credit losses in the portfolio of a particular bank. Banks seek to protect themselves from credit risk by many approaches of which the upstream approach, by assessing the risk against different criteria and techniques. After that, they evaluate it using different tools of protection (risk recovery) to minimize or even eliminate the risk. The loan guarantee is one of these risk recovery tool.

Our study is about risk assessment. The assessment of credit risk involves the question of the solvency of the borrower. This solvency depends on factors called "Endogenous", which means internal factors relating to the borrower, and factors called "Exogenous" that deals with the contextual factors relating to the borrower's background.

Several approaches are used to evaluate the repayment default in the credit risk. These models were designed to estimate the probability of default and to estimate the loss caused by the credit default. Some models are used (especially for individuals loans) as a support to the final decision of approval or rejection of the credit. We will outline the main models that covers these objectives.

Rating Based Models

The credit rating based systems try to integrate financial information about companies. This information can be about administration, human resources, vision, strategy and market positioning against competition. After the collection, it is implemented in a rating system where each component is rated according to its weight, and therefore reach a final rating expressing the company's condition. The rating models consist in two categories:

- External Credit Rating

An external rating is an assessment made by a credit rating agency (CRA, also called a rating service), whom assigns credit ratings, which rate a debtor’s ability to pay back debt by making timely interest payments and the likelihood of default (Vairava, 2012). The ratings of medium term (over a year) or long-term (10 years or more) can range from AAA (triple A), the highest credit quality and degree of safety, to D, the lowest quality and the company is in default or expected to default. The short-term rating is to force the obligor's capacity to meet its commitments to one year. The long-term rating considers the company to meet its obligations within a year (HAND, 1997). The higher the score the better. Appendix 1 details the long-term and short-term ratings scales that the three major rating agencies give. The criteria on which these agencies base their rating depends on the mission entrusted. For enterprises, they have financial criteria related to management, economic situation, stability, monetary and fiscal policy etc.

Moreover, the authorized agency has access to all official documents of his client (CANNER, 1991). The initial process will last several weeks under contacts and intensive analysis, after which the agency gives ratings to its customer. At this stage, the unsatisfied customer can simply reject it, in which case the note will not be published, the contract will most probably be broken with the agency, and a commission payment will be prepared based on the contract. However, If the contract was maintained with the agency (and the scoring was published), the agency may review the rating at any time, either following the occurrence of a particular event (economic, loss sudden customers...) or following a regular customer visits (usually at least once a year). The review may result in a change in scoring (increase or decrease).

- Internal Credit Rating

Banks must have procedures to classify the creditworthiness of companies and retail clients. The ratings issued by the agencies are only available to relatively large industrial customers. The Small and Medium Enterprises in their overwhelming majority are not publicly traded and thus they are not classified by the rating agencies. The approach based on internal ratings (IRB approach) in Basel II allows banks to use internal ratings to determine the probability of default (PD) of their credits (A.M. FEATHERSTONE, 2006).

The approaches of internal ratings and default probabilities involve as usual profitability ratios (such as return on assets) and the ratios derived from the balance sheet (as the current ratio and the equity ratio debt / equity). They often use the financial information provided by a company and study their changes allowing them to estimate the degree of simplicity of the debt of a business service (ARMINGER, 1997).

Rating systems allow the sharing of the assessment of credit risk with potential investors (or creditors) without the need of having access to financial and administrative information regarding a specific company. However the use of these systems requires that the financial information is complete and transparent, which unfortunately is not always the case. Moreover, rating systems cannot be applied to SMEs for two main reasons. First, SMEs are not enlisted in the stock market. Their capital is limited compared to large enterprises and they do not fulfill the conditions that make them candidates for the examination and the rating by external credit agencies. Similarly, the costs of ratings are high relative to their financial capacity. Second, SMEs suffer from lack of financial transparency in most developing countries. In the Lebanese context of our study, the financial information is somehow blurred, often poorly presented, due to the lack of legal framework to indulge professional financial accounting practices. The only Lebanese businesses that benefit from rating systems are some banks like Alpha group (who have bank deposits exceeding 2 Billion US Dollars) and the Lebanese state due its high indebtedness and its issuance of national currency cash tokens and government bonds in foreign currencies (Eurobonds).

Credit Scoring Models based on Financial Accounting ratios

The credit scoring is a set of credit assessment models that have financial ratios extracted exclusively from the accounting data to predict business default. Fitzpatrick (1932) was one of the pioneers to use this approach and established the existence of a relationship between the probability of default and certain financial characteristics of the company. The ratios used in the models of the "Credit Scoring" can be classified into Profitability ratio, Financial Leverage ratio, Debt/Equity Ratio, Growth Ratio and Liquidity Ratio. Accordingly, we can have a large number of possible financial ratios that can be used as explanatory variables in the credit scoring models. Typically, the variables are those with the highest predicting power to explain the default rate after performing analyzes of univariate variances. The predictive power of each variable can be evaluated using different methodologies. We will use in our study a most common model, therefore easily adaptable to the context of SMEs.

The Altman Z-score

The Altman (1968) Z-Score is considered one of the most common and used applications of the "Credit Scoring". Some banks are adopting it in their internal rating systems. The Z-score uses a statistical technique known as the Discriminant Analysis (DA), which attempts to predict bankruptcies from five ratios used as explanatory variables. These ratios are:

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings Before Interest & Tax / Total Assets

X_4 = Market Value of Equity / Total Liabilities

X_5 = Sales / Total Assets

Therefore, the Z score is calculated as follows:

$Z - score = 1.2X_1 + 1.4X_{2+}\ 3.3X_3 + 0.6X_4 + 1.0X_5$

Altman has found that score below 1.8 implies that the company will probably go bankrupt, while companies with scores above 3.0 are not likely to go bankrupt. In multiple studies, the Z-Score generates 72% of accurate predictions two years before the bankruptcy event, with a Type II error 6% (Altman, 1968) but the number of businesses is limited. In a series of subsequent trials of three different periods during the post 31 years (until 1999), the model was considered accurate at 80-90% of bankruptcy prediction a year before the event, with a type II error (classification of the bankrupt company beforehand) of about 15-20% (Altman, 2000). From 1985, the Z-score was widely accepted by Audit firms, management accountants, and the databases used for the evaluation of loans. The formula has been used in a variety of contexts and countries, although it was originally designed for public companies with assets value of more than $ 1 million. In Later studies, several variations were designed by Altman to be applicable to private companies (the Z'-Score Altman) and non-manufacturing firms (Altman Z ''-Score).

The popularity of the Z-score can be explained by its conservative and rigid approach on one hand, and the ease and speed of its introduction and implementation in banks and financial institutions on the other. However, like any models based on accounting and financial data, limitation of these models is based on two facts:

First, the existence of assumption of financial and accounting information: The model cannot estimate the failure of a start up or a company that does not have regular accounting and financial information. The non-transparency or opacity of such information may bias the model.

Second, models, based on accounting, analyze historical performances; this does not mean that performance will be repeated. In addition, the measure of volatility, which is a major contributing factor to the probability of default of a business, is generally not included as an explanatory factor in the Z-Score. This omission is made to obtain reliable measures of volatility. However, the use of quarterly or annual data streaming process is difficult to obtain. In Lebanon, this problem is exacerbated by the lack of legislation on financial accounting (no accounting law) and little control over the tax returns of companies, especially SMEs, which encourages no financial transparency. Therefore, the communication and dissemination of information to stakeholders, including creditors, is not clear.

The Hybrid Models

Hybrid Models are systems and credit risk estimation based on a combination of public and private information of the borrower formed by opinions and judgments. This information is subjective and is obtained either by the investigations from borrowers (as explored in scoring), or by the bank. For loans granted to SMEs, the hybrid approach is the most appropriate given the nature of the often relational and non-bank institutional relationships with SMEs. The following section describes the hybrid model.

- Expert Systems

In terms of credit risk analysis, expert systems seek to reproduce consistently experts' decision rules for loans, bringing experts' practices together and asking them to validate the rules of credit decision. The set of rules will then be used to describe the risks of the borrower and assign him a certain rating. The objective of expert systems is to set up expert rules to identify and measure the borrower's risks, and then to use these rules into operational decision systems. There is no standard approach for expert systems, several variations and categories exist:

• Expert systems based on financial analysis that combine the professional opinion of financial scoring systems as the Altman Z-Score. In this case, the role of the expert system is to interpret and analyze the financial numbers. Either if the loan officer has the score, he can still interpret and grant credit even if the score is not desirable.

• Expert Systems based on the Classic Anglo-Saxon approach called the five Cs (Character, Capital, Capacity, Collateral and Conditions). That is to say, the constitution and the consideration of an application containing all documentation relating to the borrower, financial structure and guarantees provided.

• The existing expert systems for retail credits. They are used in the analysis of consumer loans (personal loan, car, housing etc.), especially dealing with qualitative information on the personal situation of potential borrowers of this type of loans.

All these expert systems have three types of information:

1) Details of the borrower (age, sex, years of experience, reputation, relational seniority with the bank)

2) Information on the financial characteristics of the borrower (financial structure, sources of income, debts status, level of profitability and stability, financial policy, level of guarantees etc.)

3) Information of the contract or the borrower's business sector (positioning of the borrower's product in the market, the degree of competition in the same industry, the sector's position in the economic cycle etc.)

Expert systems are distinguished by their use of qualitative elements; however, they still incorporate some quantified standards. They are easily understandable because they reproduce the credit expert reasoning. These systems integrate exogenous elements of the borrower (Environment and Sector) with their financial variables. They contribute to the accuracy of the risk assessment, where models based on purely quantitative data have difficulties to integrate or manage qualitative information for statistical reasons such as collinearity problems. The flexibility of expert systems is that they do not require lengthy historical data, such as the scoring system.

However, expert systems are constructed subjectively, to the extent that certain information is obtained by direct interviews with experts. Therefore validating the expert systems is carried out retrospectively. From the fact that expert systems are based on the experience of the expert, it is difficult to scientifically test results provided by these systems, as opposed to purely quantitative models that can have multitude of statistical inference tests. The only approach that seek to improve the performance of expert systems would be by recovering the elements from the market to reintegrate them with the components of the system feedback process. This is what the practical part of this study will attempt to perform.

To close the parenthesis on the Credit Risk assessment methods by relating it to the subject of our study (SMEs) we can conclude that:

• Economic models generate estimations where conclusions can be drawn and integrated into expert and scoring systems. It can give indices related to sectors or regional default, but cannot be applied to loan applications to SMEs as they are very general and do not take macroeconomic values.

• The external ratings based models work with large enterprises, often listed in the stock market. The process is long and expensive. The overwhelming majority of the SMEs cannot use it.

• Models based on the elements of financial accounting have limitations on the availability and transparency of financial information provided by SMEs. These models are not indicative in countries where the legal framework of financial reporting is limited and sometimes outdated. In Lebanon, the use of these models is limited to large enterprises (by Lebanese standards) and to large taxpayers who can demonstrate some financial transparency.

• The most suitable models for SMEs are mixtures of personalized scoring systems and expert systems that combine knowledge and experience. However, these practices should receive continuous updates for their scoring systems. As a starting point, this update includes the analysis of field observations, which means the loan performance analysis mainly for defaulting.

3. The Basel II Reform and the provision of Finance for SMEs Projects

The year 2006 marked the peak of the reform of the international solvency ratio, implemented since 1990 by the Basel Committee, on one hand, and the evolution of financial markets and supervisory environment of credit institutions on another hand. This has led to the development of measurement techniques and devices for bank risk management. These techniques are based on three pillars:

1- Improved risk calculation and therefore adjust their coverage by minimum capital requirements;

2- The supervisory review process: refining the judgment given by the Pillar 1

3- Market discipline: to improve financial transparency to strengthen market discipline and encourage the adoption of good risk management practices.

We are interested in the elements of the first pillar that address calculation risk: types of risk are risk related to credit, market and operations. The loan default, the main element of our study is part of the credit risk. Three approaches are proposed to the credit risk:

• The standardized approach (SA), based on the use of external credit ratings; for bank commitments to businesses, it requires a table of correspondence between the rate assigned by an external credit assessment institution (ECAI) and weights proposed under Basel II

• Foundation Internal Ratings-based approach (FIRB)

• Advanced Internal Ratings-Based approach (AIRB)

IRB approaches require measurement by the banks themselves for their exposure to credit risk from various parameters. Which means the probability of default of the borrower, loss due to default, and exposure to default and the remaining period of the loan. In the FIRB approach, the institution considers only the probability of default, other parameters being set by the Basel Committee, while in the AIRB approach, the enterprise itself must estimate these parameters.

For enterprises, the Basel II recognizes the specific characteristics of SMEs and provides a more detailed breakdown of the loans issued. Specifically, the new rules criteria is related to the enterprise size, in terms of annual turnover and the amount of loans granted. The corporate portfolio (large enterprises) includes all companies whose turnover exceeds EUR 50 Million. The SME portfolio corresponds to companies whose turnover is less than EUR 50 Million. It is then allocated either to the portfolio within the retail banking (SME-retail) or to the credit portfolio companies (SME-corporate), given that the amount of credit allocated is less than or greater than EUR 1 Million. In general, a more favorable weighting is allocated to SMEs. First, due to the importance of their role in the economy, and second, due to the relative lack of correlation between the defects that may affect small businesses. However, a default recorded for large companies could have ripple effects and a much wider impact. Specifically, the loans granted to "small-retail" justify lower capital requirements due to greater diversification recognized by this activity which results in a strong pooling of credit risk.

Under the standard approach, the new rules provide a table of correspondence between the external credit rating assigned to the counterparty by an external credit assessment institution (ECAI) and risk weights used to calculate equity requirements. As already indicated, the regulation of Basel II included a weighting of 100% for all loans to businesses. A weighting of 75% is now applied to loans granted to SMEs under the retail banking (SMEs and retail). Other commitments on SMEs (SME-corporate) are weighted according to the company's external evaluation. Thus, all things being equal, the capital requirement will be five times less (20% weighting) for a credit to a company rated AAA than a credit to a company rated BBB (100% weighting).

In Lebanon, based on 9302 and 9794 decisions of 1/4/2006 14/12 of 2007, the Central Bank implemented by the circular 115 of 14/12/2007 taking the Basel II framework regarding portfolio segmentation of credits, but with differences in sizes and amounts of loans, given the specific characteristics of SMEs in Lebanon are as follows:

• The corporate portfolio (large) includes companies whose turnover exceeds 5 million US Dollars or equivalent in national currency.

• The SME portfolio corresponds to companies whose turnover is less than 5 million US dollars or equivalent in national currency. A loan to an SME shall not exceed 0.2% of the total credit portfolio value.

Having explored the elements of SMEs financing along with different approaches in estimating the risk of default of credit in general and SMEs in particular, we turn to the specific context of our study, which is small and medium Agro-Food enterprises in Lebanon, their financing and guarantee.

C. Overview of the SMEs loans guarantee programs in Lebanon

SMEs have an important role in the economy, especially in a country where SMEs constitute the major share of the market. Therefore, banks were encouraged to take advantage of the availability of these SMEs by facilitating access to finance. Law No. 24/1999 was promulgated to let the National Institute for Guarantees of Deposits Sal (NIGD) participate in the funding of a Lebanese Limited Company called “KAFALAT SAL” whose main purpose is to guarantee loans to small and medium enterprises (SMEs). This law has established "KAFALAT SAL" and set the first official definition to identify the SMEs in Lebanon.

KAFALAT S.A.L. is a public company whose private law No.24 / 1999 has enabled its establishment, formed by the cooperation of two public and private sectors; the capital share of KAFALAT is 20 Billion L. L. However, KAFALAT is a financial institution that meets the law of a private company in Lebanon. Therefore. KAFALAT is considered a for-profit organization. It is subject to taxes on income and reporting obligations with the Lebanese Central Bank (BDL) and the Banking Control Commission of Lebanon (BCCL). KAFALAT is required to comply with financial laws and any circulars or instructions issued by the BDL. However, the ultimate goal of positive results is not the distribution of dividends, but the organic increase in KAFALAT's capital to strengthen the structure of its equity.

KAFALAT guarantee loans granted by commercial Lebanese banks to SMEs operating in Lebanon, which constitute one third of all SMEs operating in general. The majority of SMEs consist of purely commercial activities or services. SMEs include agriculture and livestock, industry, crafts, tourism (restaurants, hotels with daily rates) and technology industry. These activities are different from purely commercial activities or services by their opportunities of high benefit and job creation. However, these activities require higher investments and medium to longer periods, which makes its financing at an adequate size and duration necessary. The duration of a loan secured by KAFALAT can reach up to 7 years (can go up to 15 years with the Energy Program), with the benefit of a grace period up to 12 months.

1. Requirements for granting the KAFALAT guarantee

The requirements needed to provide a KAFALAT guarantee to an SME candidate applying in a Lebanese commercial bank are divided into five major steps. The SME places a KAFALAT loan application by his bank after its approval. This application contains all the information need for a loan, including the name and nature of the candidate, his required amount, loan purpose, loan term, grace period, the business plan and the feasibility study and the candidate's financial reports (if available) and other documents or evidence relating to the items mentioned. The application is then studied and the data analyzed following policies and procedures specific to each bank. The majority of Lebanese banks use the expert systems in the analysis of their applications. Following their assessment and the score obtained from the final decision of the loan committee of each bank, loan is either accepted or rejected. If the loan is accepted, the corresponding application is then transferred to KAFALAT with all the documents listed above, in addition to the analysis, the risk report and the approval letter granted by the bank. KAFALAT then receives and analyzes the approved loans by its own credit officers. At this stage, it would use of all the documentation and investigation provided by the bank or the borrower to fulfill its duties of good care. The project is reviewed and KAFALAT uses the expert system that combines financial analysis (if available), the analysis of the project, and field reports, all integrated in a one rating system. A credit committee reviews the result where they give the final decision to either grant or reject the guaranty. A rejected application cannot be guaranteed and consequently could not be granted a KAFALAT loan by the lending bank. Once accepted, the decision is communicated with the bank and an issue date is assigned. The customer will be called by his bank to sign the loan agreement. KAFALAT issues a letter of guarantee in order of the lending bank, ensuring the loan from its date of issuance for a specified amount, period and determined coverage and an annual premium of 2.5% of the coverage value of the loan plus interest. This premium is accounted annually for the whole duration of the loan on the remaining value at the end of each year. In case of loan default, KAFALAT intervenes and executes its guarantee. Loans secured by KAFALAT cannot be used to repay existing debts prior to acceptance. Similarly, KAFALAT is not involved in the process of decision making at the bank to approve the loan before its submission. KAFALAT doesn’t require any additional collateral from the borrower. However, if the bank does, like obtaining additional collateral and mortgage, KAFALAT will consider it for the recovery of the remaining debt in proportion and collaboration with the bank.

2. KAFALAT Programs

KAFALAT offers eight loan guarantee programs for Small and Medium Enterprises based on each applicant requirements. However, the three main programs that were most commonly used are:

a- KAFALAT BASIC: the first program to start in year 2000. It offers 75% guarantee coverage of the value of the loan for amounts ranging between LBP 5 Million and LBP 300 Million or currency equivalent in USD or EUR.

b- KAFALAT PLUS: covers 85% of the value of the loan for amounts ranging between LBP 5 Million and LBP 600 Million or currency equivalent in USD or EUR. These loans are given to companies only (SARL and SAL only).

c- KAFALAT INNOVATIVE: covers 90% of the value of the loan for amounts ranging between the equivalent of LBP 15 Million and LBP 300 Million (loans are granted exclusively in Lebanese Pound). These loans are provided only to companies recently formed (SARL and SAL). Moreover, they should be undertaking projects of innovations in technology, new products, and new inventions.

3. Evolution and Performance of KAFALAT Program

Since its launch in June 2000, the volume of activity in the Lebanese banking portfolio continues to increase, going up from 33 guarantees with a value of 1.9 billion Lebanese Pounds to over 12,965 guarantees with a value of 1456.3 billion Lebanese

Pounds. KAFALAT's capital were around LBP 20 Billion in 2000 and increased to 78 Billion LBP end of 2015. However, although the losses caused by defaulted loans and guarantees executed to these loans, KAFALAT was able to increase its capital dramatically. The organic equity growth is essential to the continuation of the activity of KAFALAT, which does not benefit from subsidies or shares of state budgets.

Before the changes made by the reform of Basel II, KAFALAT guarantee was equivalent to cash collateral, therefore the guaranteed loan was zero risk based on the coverage percentage. With the changes made by Basel II, KAFALAT was concerned about evaluations and ratings to determine the corresponding weight of the risk related to each credit. In fact, Lebanese banks, despite the system implemented by the 9302 decision of 1/4/2006 to adhere standards implemented by Basel II on the horizon of 2008, benefited from a 1-year delay, and up to this day, they still use their integration measures and launching procedures to meet the conditions stipulated in decision 9302.

CHAPTER III

RESEARCH STRUCTURE AND METHODOLOGY

This chapter explains the most common techniques used in predicting the determinants of loan default. In further sections, we develop suitable methodology for modeling the probability of default in loan by using the logistic regression method.

A. Common techniques

In the previous literature, we explored many common predicting methods to study the determinants of loan default. Out of these, the discriminant analysis (DA) or Linear Discriminant Analysis (LDA), Linear Regression (OLS) and Logistic Regression (LR). Credit Scoring Models (CSMs), as stated previously, are analytic techniques that combine historical and current information to make prediction about whether the borrower will default or succeed in repaying his loan. The Neural Networks (NN) and Classification Trees (CT) were also used as credit scoring techniques. We will briefly explain and summarize the choice of our model in this study.

Many studies compared different methods concerning credit risk. For example, a study by Arminger et al. (1997), compared CT analysis, LR, and NN based on a large dataset from a bank in Germany that issue consumer loans. The results show that the predictive power is equivalent for all techniques. However, they considered that LR was the best one due to its better performance in contrast to the NN and CT. Moreover, Desai et al (1996) have compared NN, LR and LDA. Their study was to build credit-scoring models and then define the predictive power of these models. Their dataset covered periods between 1988 and 1991 from multiple credit unions in the United States. The results obtained were indefinite. The LR and NN approach were almost the same. However, LR does better than the LDA model. In this study, the significance of variables was not included and these three models estimated to the same rating between default and non-default customers. In a different study, Kocenda and Vojtek (2009) studied the LR and CT techniques. The results of both techniques provided significant results and created good models. Although this study indicates that the latter techniques have good estimates, many evidences proved that LR is the best in estimating and determining loan default predictors and probability (Luo and Lei 2008 and Yang et Al, 2009). Hand and Henley (2007) claim that the best method depends on the problem in study and its details. They claim that LR is easy to understand and is more attractive to be used. Many studies claimed that, as an empirical mode, logistic regression has high predictive power. For example. Kocenda and Vojtek (2009) and Thomas (2000), used LR in their studies to analyze credit default. Therefore, the most common technique for estimating default risk is the LR.

In contrast, many studies criticized logistic regression due to its failure in assuming linearity in relationship between the independent variables. However, Chen and Huang (2003) prove that credit-scoring datasets are only slightly non-linear and LR therefore gives appropriate estimates. Logistic regression is as good as the Neural networks when the performance measure is the ratio of good and bad loans (Chen & Huang, 2003). An important evaluation measure for CSM is the correct classification of the percentage of bad loans.

It is obvious that all the above methods are acceptable when used in their proper studies. According to Altman and Saunders (1997), LDA and LR are the most dominant methodologies. Both models gave similar results in a study by Martin (1997). In our study, we will use the Logistic Regression method as our CSM because most of our variables are categorical which contradict the assumption in LDA as normally distributed variables.

B. Logistic Regression

After testing all the potential variations that would allow us to have a better understanding of the dynamic links between the loan default risk and the different qualitative variables, we apply a logistic regression model. A Logistic regression model (also called Logistic or logit model) allows us to establish a relationship between a binary outcome variable and a group of predictor variables.

Following Glennon and Nigro (2005), we model the default process as a probabilistic outcome, and we use the Logistic Regression framework to predict the correlates of the loan default probability. According to Hosmer and Lemeshow (1989), we use logistic regression when the study is dichotomous (Success vs default). This analysis provides us with predicted probabilities of defaulting for combinations of the independent variables. Moreover, as per Draper & Smith (1981), regression provides a useful mean of analyzing outcomes that were unknown. In this framework, the dependent variable we are trying to evaluate is not a continuous one, as we are predicting the likelihood that *Y (loan status)* is equal to 1 (Default) rather than 0 (Success) given certain values of *X*. That is, if *X* and *Y* have a positive linear relationship, the probability that a firm will have a score of *Y* = 1 (i.e. defaults on its credit) will increase as values of *X* increase. *X* here is a set of predictor variables that affect the default probability (categorical or dummy variables).

In logistic regression, the logistic probability that *Y* = 1 is referred to as p (as the probability of Default). The probability that *Y* is 0 is therefore 1 – p. If we know the regression equation, we could theoretically calculate the expected probability that *Y* = 1 for a given value of *X*. The logistic probability can be expressed as follows:

$$p = \frac{e^{(Vi)}}{1 + e^{(Vi)}}$$

where *Vi* is a latent variable that is conditioned on a set of covariates that are suspected to influence the probability of default. In our model, *Vi* is specified as follows:

$$V_i = \sum_n \beta_s \times s_{ni} + \sum_s \sum_k \beta_{sk} \times x_{ki} \times s_{ni}$$

Where β_s is a sector specific constant term, evaluated at the mean value of all the continuous variables and x_{ki} is the set of covariates that are interactive with each other. β_{SK} is the parameter that represents the effect of covariates x_{Ki} specific to the S sector. In Table 1 we display all the significant Dependent and Independent Variables used in our model.

Table 1 Variables used in the estimation model

	Variables	Description
Dependent Variables		
Y	**1 - Loan Status**	Binary Variable - The status of the loan
		0 if loan is Successful; 1 if defaulted
Independent Variables		
s_n	**2 - Sectors**	Binary Variable - The loan economic sector
	Agriculture	1 if loan is in Agriculture ; 0 otherwise
	Crafts	1 if loan is in Crafts ; 0 otherwise
	Industry	1 if loan is in Industry ; 0 otherwise
	Technology	1 if loan is in Technology ; 0 otherwise
	Tourism	1 if loan is in Tourism ; 0 otherwise
x_k	**3 - Loan Period**	Continuous Variable / Loan duration in months
	4 - Loan Amount	Continuous Variable / Loan Amount in USD
	5 - Guarantee Program	Binary Variable
		70 & 75% guarantee program = 1
		85 & 90% guarantee program = 0
	6 - Regions	Binary Variable - The location of the business
		Beirut & Mount Lebanon = 1
		Bekaa, North & South = 0
	7 - Borrower's Type	Binary Variable - The legal form of the business
		Sole Proprietorship = 1
		Partnership & Company = 0

C. Dataset description

The dataset analyzed comes from the internal database of KAFALAT, the only existing financial company in Lebanon offering loans guarantee for banks. KAFALAT issues letters of guarantee to Lebanese commercial banks that provide records on geographical areas all over the Lebanese territories, on all types of entrepreneurial Small and Medium Enterprises, and on loan Maturities going up to 10 years. Among 50 major commercial banks operating in Lebanon, around 35 deal with KAFALAT.

Our data sample consists of 6,757 granted loans between 2001 and 2015. Out of these, 82% performed well and 18% defaulted. The collected data includes information about:

1. Loans characteristics (Loan amount, interest rate, loan period, and grace period)
2. Borrower Characteristics (Business legal form, economic activity sector, and geographical location of the business)

These factors would help us assess the firm's solvency risk by using them to develop better estimates of KAFALAT's exposure to loss over time. This information helped us report descriptive statistics by default experience for a selected set of loan characteristics over a specific loan period. We were able to determine the total number of loans guaranteed and the loans that were defaulted based on sectors, regions, type of borrower and guarantee program.

CHAPTER IV

EMPIRICAL RESULTS AND DISCUSSION

This chapter presents the data for our empirical study and analysis. After describing the dataset, we shall explain the variables used in the model giving some descriptive statistics about them and explain how those variables affect the model.

A. Descriptive Statistics

Table 2 below gives us the descriptive statistics for our sample loans. Over the period 2000-2015, KAFALAT issued and closed 6,757 loan guarantees, out of which 1,255 loans defaulted.

Table 2 Descriptive Statistics for the Sample

	Successful Loans			**Defaulted Loans**			**Total Loans**		
	Mean	**SD**	**min - max**	**Mean**	**SD**	**min - max**	**Mean**	**SD**	**min - max**
Loan Amount (Millions USD)	96,492	68,186	2,000 – 400,000	134,401	69,280	6,667 – 400,000	103,533	69,957	2,000 – 400,000
Loan Period (Months)	71.00	18.08	6 – 134	83.24	15.69	24 – 133	72.99	18.33	6 – 134
Grace Period (Months)	7.77	3.81	0 – 36	9.36	3.63	0 – 18	8.07	3.83	0 – 36
Interest Rate (%)	4.85	2.98	0 – 11.21	4.79	2.43	0 – 10.86	4.85	2.89	0 – 11.21

From this table, it is clear that the average period of a loan issued and closed is around 73 months. The average amount of a loan granted to borrowers is approximately 103,533 USD. The mean grace period is 8.07 months. During this period, the minimum amount of loan granted to a borrower was around 2,000 USD while a maximum was

400,000 USD. Average duration for a loan to mature was 6 months while the maximum number of months for loan duration is 134 months. The average for loans that have defaulted is 83 months with an average loan amount of 134,401 USD. The average grace period was around 9 months.

As for successful loans, applicants who succeeded in fully repaying their loans on time, the average loan period was 71 months with an average amount of 96,492 USD. This is less than the average in defaulted loans, which suggests that longer periods' applicants are more likely to default in their loan repayment. Their average grace period is 7.77 months with an average interest rate of 4.85%.

Table 3 below gives us the default rate among all the categorical variables that we used in our study.

Table 3 Default rate among Sectors, Regions, Type of Borrower and Guarantee Program

Variables	Variables	Success (0)	Default (1)	Total	Default /Total loans	Default /total Default (1255)
Sectors	Agriculture(1)	2095	374	2469	15.1%	29.8%
	Crafts (2)	172	34	206	16.5%	2.71%
	Industry (3)	2415	500	2915	17.2%	39.84%
	Technology(4)	117	24	141	17%	1.91%
	Tourism (5)	703	323	1026	31.5%	25.74%
Regions	Beirut (1)	386	129	515	25%	10.28%
	Bekaa (2)	996	177	1173	15.1%	14.10%
	Mount Lebanon (1)	2583	614	3197	19.2%	48.92%
	North (2)	590	192	782	24.6%	15.3%
	South (2)	947	143	1090	13.1%	11.39%
Type of Borrower	Sole Propietorship (1)	2019	640	2659	24.1%	51%
	Partnership (2)	3008	557	3565	15.6%	44.38%
	Company (3)	475	58	533	10.9%	4.62%
Guarantee Program	Basic (75%) (1)	5082	838	5920	14.2%	66.77%
	Plus (85%) (2)	412	402	814	49.4%	32.03%
	Innovative (90%) (2)	8	15	23	65.2%	1.2%
Loan Amounts	2,000$ – 100,000$	3429	508	3937	12.9%	40.48%
	100,001$ - 200,000$	2074	734	2804	26.17%	58.49%
	200,001$ - 400,000$	2	14	16	87.5%	1.12%

From table 3, we can see that the default rate in tourism is two times higher than the default rate in other sectors. The default rate in tourism is 31.5% while that of Agriculture 15.1%. However, Agriculture form more than 29% of defaulted loans in contrast to tourism that forms 25%.

According to regions, default rate for borrowers in Beirut and North is around 25% against 19.2% in Mount Lebanon, 15.1% in Bekaa and 13.1% in South. Thus, Beirut and Mount Lebanon together form more than 55% of total loans and more than

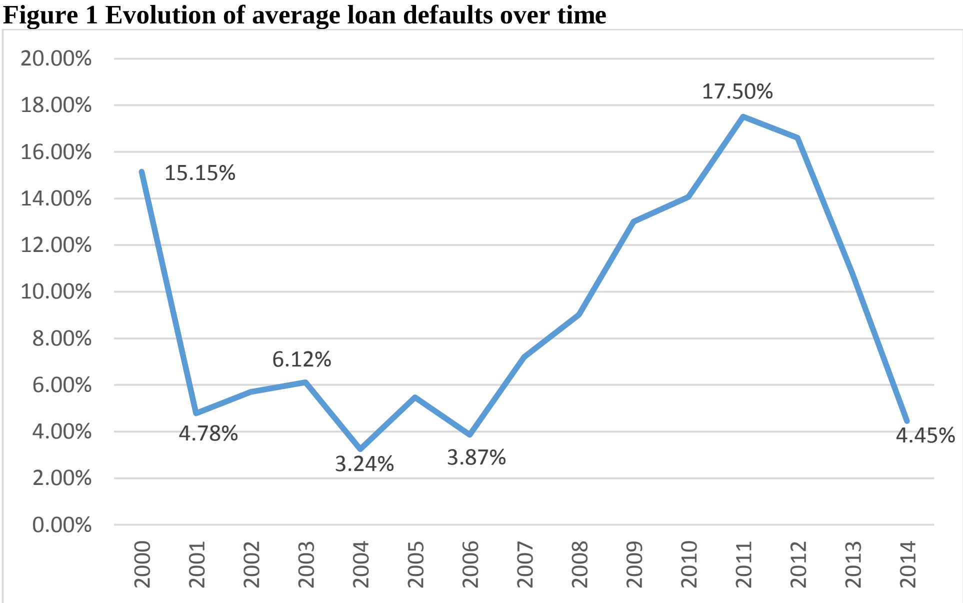
59% of defaulted loans. Interestingly, we can notice that in the South we have a low default rate of 11.39% of defaulted loans knowing that in 2006 many economic sectors were affected negatively by the war and caused the closure of many private businesses.

Among the type of borrower category, default rate is high for borrowers that have a legal form of Sole Proprietorship with a rate of 24.1%, followed by Partnerships with a rate of 15.6% and Companies with the least default rate of 10.9%.

As for the guarantee programs, in the basic KAFALAT program, we can see that this program forms more than 66.7% of the total defaulted loans. However, the innovative program has the highest rate of default of 65.2% in comparison to 14.2% in Basic Program and 49.4% in Plus Program.

We can notice that the loan default rate is higher for loans that range between 100,001$ and 200,000$ marking a default rate of 26.17% in contrast to smaller loans that have a default rate of 12.9%.

Figure 1 Evolution of average loan defaults over time



Since its initiation, the default rate on KAFALAT loans has been decreasing with fluctuation between 2000 and 2006, from 15.15% to 3.24%. However, starting from 2007 the default rate has increased from 3.87% to reach the peak of 17.5% in 2011. In 2012, the default rate has been declining, from a high of 16.61% to almost 4.45% in 2014 (Figure 1). According to a previous constructed by Madani (2009), this effect was due to increased experience of credit management of both banks and the guaranteeing institution in screening applicants and identifying loans. However, according to the historical analysis of KAFALAT's loans, this decrease is due to loans that are still in process which status is still undetermined. Therefore, an absolute conclusion regarding this decrease is irrelevant, knowing that the number of loans that are still in process is very large (3,475) between 2011 and 2015.

B. Model Selection

In order to capture the best model for our study, we tested two models. From our variables list, two variables (loan period and loan amount) are highly correlated and hence may be a source of multicollinearity. In Model 1, we used 6 variables in addition to loan period. We can see that the log likelihood is equal to -2,706.10. In Model 2, we used the same 6 variables in addition to loan amount. We get a log likelihood of -2,878.13. In order to choose the best-fit model, we choose the model that has the higher log likelihood. Based on the findings of Featherstone et al. (2007), loan size does not significantly affect whether the loan will enter default status or not. Therefore, we chose model 1 with loan period variable.

We will explore in the next section the variables that proved that our model has a good fit.

C. Model Estimates

Table 8 model 2 in the Appendix presents the results of the logistic model estimation of all the variables. These estimations were the results of the statistical analysis performed using STATA. Therefore, we can deduct the predictive power and contribution of each of the variables. From these estimations, we found out that the two variables “Grace Period” and “Interest Rate” were highly insignificant in contrast to other variables. Therefore, we excluded them from our final model.

Table 4 below presents the logit model estimates and odds ratios.

Table 4 Logistic regression estimates of determinants of loan repayment default by sectors

	Coef	SE	Odds Ratio	P-value
Sectors				
Agriculture	-0.309	0.422	0.734	0.464
Crafts	1.246	1.072	3.478	0.245
Industry	-0.329	0.172	0.719	0.056
Technology	0.475	1.387	1.608	0.732
Tourism	0.079	0.27	1.082	0.771
Loan Period				
Agriculture	0.05	0.005	1.052	0
Crafts	0.061	0.018	1.063	0.001
Industry	0.052	0.004	1.054	0
Technology	0.028	0.017	1.028	0.095
Tourism	0.043	0.006	1.044	0
70% & 75% Program				
Agriculture	-1.594	0.415	0.203	0
Crafts	-2.823	1.03	0.059	0.006
Industry	-1.645	0.137	0.193	0
Technology	-3.182	0.8	0.041	0
Tourism	-2.025	0.196	0.132	0
Beirut & Mt Lebanon				
Agriculture	-0.293	0.133	0.746	0.028
Crafts	-0.785	0.437	0.456	0.073
Industry	0.094	0.119	1.099	0.43
Technology	-1.032	0.844	0.356	0.222
Tourism	0.407	0.198	1.503	0.039
Sole Proprietorship				
Agriculture	-0.322	0.332	0.725	0.333
Crafts	-0.165	0.628	0.848	0.793
Industry	-0.383	0.13	0.682	0.003
Technology	0.471	1.277	1.602	0.712
Tourism	-0.173	0.205	0.841	0.398

Looking at the model estimates in the table 4, first, the sector results suggest that as a sole proprietorship in Beirut or Mount Lebanon under guarantee level of 70 or 75 % and under an average loan period of 73 months, we would expect that Agriculture and Industry are less likely to default. However, it is more likely to default in Crafts, Technology and Tourism.

Since loan period is a continuous variable, the coefficients we obtained represent the difference in the predicted value at which a loan can default for each additional month in the loan period, if all else are held equal. According to our coefficients, loan period is significantly increasing for all sectors. The largest of these is for Crafts followed by Industry, Agriculture, Tourism, and Technology. This means that the loan default probability is more likely to increase with every additional month in the loan period. Technology, however, is only significant at p-value 0.095. Therefore, our data shows that the longer the loan length period, the higher the probability of default. This only depends on the nature of the project. For example, for trees projects, KAFALAT has issued new programs were they cover loans up to 10 years (called KAFALAT Agriculture) due to the delay in production caused by the trees growing. They need around three years to start producing in good quantities. Therefore, it is essential to have longer period than other projects, which would not mean that these projects would default and give them higher chances of success.

As for regions, we would expect that loan in agriculture, being significantly less than one, is less likely to occur in Beirut or Mount Lebanon than in other regions. According the market data, around 42% of agro-food enterprises are located in Beirut and Mount Lebanon. However, holding all variables constant, significant positive coefficients for tourism in Beirut or Mount Lebanon. This means that it is more likely for a loan to default if it is issued for a tourism project in the Beirut and Mount Lebanon region, under the mean loan period of 73 months in the Basic KAFALAT program category.

Another interesting predictive result related to the guarantee programs shows significance for all sectors under plus and innovative programs category. Having the coefficients value significantly negative, the probability of a customer to default in a loan repayment is less likely to occur under the Basic guarantee program category for all sectors, holding all conditions the same.

The loans are further analyzed according to the borrower's legal structure or type. The estimates show that a loan is less likely to default in the industry sector at a significant negative coefficient. If the loan issued is for a borrower with a sole proprietorship legal entity, holding all-else equal, he is less likely to default than being in a partnership or a company legal entity under the same conditions.

D. Profile Analysis

Further, we simulate probabilities of default for different borrowers profiles focusing on the Agro-Food Sector. We present three profiles of which first profile A where loan period is short (30 months), profile B where the loan period is at the mean period (73 months) and profile C with a loan period of 100 months. The probabilities of default are shown in the below table 5, 6 and 7.

Table 5 Profile A - 30 Months loan period default probabilities

Profile A 30 Months Loan Period	Agro-Food Partnership or Company Bekaa, North, or South Plus or Innovative Prog	Agro-Food Partnership or Company Bekaa, North, or South Basic Program	Agro-Food Partnership or Company Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Partnership or Company Mount Lebanon or Beirut Basic Program
	9%	2%	7%	1%
	Agro-Food Sole Proprietorship Bekaa, North, or South Plus or Innovative Prog	Agro-Food Sole Proprietorship Bekaa, North, or South Basic Program	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Basic Program
	7%	1%	5%	1%

Table 6 - Profile B - 73 Months loan period default probabilities

Profile B 73 Months Loan Period	Agro-Food Partnership or Company Bekaa, North, or South Plus or Innovative Prog	Agro-Food Partnership or Company Bekaa, North, or South Basic Program	Agro-Food Partnership or Company Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Partnership or Company Mount Lebanon or Beirut Basic Program
	42%	13%	35%	10%
	Agro-Food Sole Proprietorship Bekaa, North, or South Plus or Innovative Prog	Agro-Food Sole Proprietorship Bekaa, North, or South Basic Program	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Basic Program
	35%	10%	28%	7%

Table 7 - Profile C - 100 months loan period default probabilities

Profile C 100 Months Loan Period	Agro-Food Partnership or Company Bekaa, North, or South Plus or Innovative Prog	Agro-Food Partnership or Company Bekaa, North, or South Basic Program	Agro-Food Partnership or Company Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Partnership or Company Mount Lebanon or Beirut Basic Program
	74%	37%	68%	30%
	Agro-Food Sole Proprietorship Bekaa, North, or South Plus or Innovative Prog	Agro-Food Sole Proprietorship Bekaa, North, or South Basic Program	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Plus or Innovative Prog	Agro-Food Sole Proprietorship Mount Lebanon or Beirut Basic Program
	68%	30%	61%	24%

The results convey three main messages. First, as expected, a substantial increase in the loan period (Profile B and C) increases the loan probability of defaulting. Important steps should be taken to mitigate losses once a default occurs. One such scheme is to implement some sort of agro-food-oriented insurance based on loan period. We saw that default is not an unlikely event in an agro-food portfolio. Second, guarantee program-related risk is probably more important than geographical location. Regions-related risks increase the probability of default from 7% in Mount Lebanon/Beirut to 9% in Bekaa, North, or South under the same program (85 – 90% Program). However, guarantee program-related risks increase the probability of default under plus and innovative program from 2% to 9% for Profile A, from 13% to 42% for Profile B, and from 37% to 74% for Profile C under the same region (Bekaa, North, or South). Third, there is a conclusive evidence that partnerships and companies are more likely to default than sole proprietorship.

The main objective of this study is to determine the risks and build expert systems based on these estimated risks to lower the losses. In the three profiles, agro-food sector is performing better in regions with higher concentration of agro-food activities. Based on our results, agro-food projects in Beirut/Mount Lebanon is riskier than Bekaa, North or South. However, borrowers that have a legal form of sole proprietorship are less risky than borrowers who are willing to start a partnership or company business in agriculture. By analyzing these three profiles, the creditor can set limits by which they can take firm insurances to minimize the risks and the exposure to default, and therefore increase their inspections before judging on risky loans based on this system. For example, the loan risk for a partnership entity to start an agricultural project in any of Bekaa, North or South, under a Plus Guarantee program (85-90%) can range between 9 and 51% if the loan repayment period fall between 30 and 73 months.

E. Overall Discussion of results

We used logistic regression to estimate a model describing the loan default probabilities. The analysis and empirical results generate major insights for a better understanding of the environment, structure and the different risk levels associated with the SMEs.

In terms of geographical distribution, the study shows a greater concentration of borrowers in the regions of Beirut and Mount Lebanon. This is due to the major geographical presence of pioneer banks that helped the launching of KAFALAT guarantee program and to its visibility in the market. The number of operating banks in Lebanon, as of year 2014, reached 71 banks. These banks attained over 1,041 branches distributed according to the geographic distribution of economic activities over the Lebanese regions (ABL, 2014). Historically, between year 2000 and 2004, two major banks have marked their strong presence in these regions where they started issuing KAFALAT loans addressing borrowers situated in geographical regions where they already have some previous experience. The geographical distribution of commercial banks in Lebanon shows that 49% of the branches that offers KAFALAT loans are present in Beirut and Mount Lebanon (BDL Report, 2014). This distribution does not improve loan quality. However, the geographic expansion of Banks reduces bank risk by allowing banks to diversify their exposure to local market risks that might face each region dependently. (Goetz and Laeven, 2015).

We can build a general idea of entrepreneurship in these regions by analyzing the default rate according to geographical regions. In Beirut and North Lebanon, the default rate is above the mean and go up to 25.05% and 24.55% respectively. This shows that there is some weaknesses in the entrepreneurial activities in these regions compared to Bekaa, South and Mount Lebanon. The performance of projects in Beirut and North are lower than that of other regions who have a positive history of entrepreneurial activity, particularly in agro-food industries.

Regarding the analysis by sectors, the default rate observed in agriculture (15.15%) show that despite the fragility of this sector, the risks of default is inferior to the risks observed in other sectors. However, the default rate relatively to the total of defaulted loans is equal to 29.8% that is greater than the observed average. One of the major reasons is the political instability in the country. The role of political risk reveals itself mainly in the tourism sector where the default rate (31.48%) shows an urgent need for political stability. Tourism projects would therefore gain stability and insurances for development and growth. This confirms the high volatility of this sector in parallel with the political instability in the region.

In terms of SMEs structure in Lebanon, sole proprietorship shows a simple business that evolves around the owner with all the implications regarding the structure, administration and management of the enterprise. This does not mean that this structure is effective. This structure is susceptible to risk of default, however less than the average identically observed in corporations and partnerships, which is a paradox for those who do not know the Lebanese context. In fact, the majority of the existing borrowers in KAFALAT's database are Limited Liability Companies (LLCs) with the required minimal capital, by the law, (LBP 5 millions, equivalent to 3,300 USD) that work with practice identically to the sole proprietor businesses. However, partnerships have a default rate (10.88%) lower than the average which is proved in our empirical results. This shows a better performance due to the structure of the business, often a family business. The majority of these companies being formed as partnership between relatives (father and son, sisters or brothers), each contributing in the company in a different field; Know-how, finance or management. This legal structure of partnerships makes every partner liable individually to the entire consequences of the business whether in profits or losses. According to these claims, some can say that partnership loans are more likely to be fully repaid successfully without defaulting despite their financial difficulties and the liquidation of the business. However, our model proved that this structure is more likely to default at a higher risk than the sole proprietorship structure.

In terms of financing and guarantees of SMEs, first, the fact that 12,965 bank guarantees were issued of which 6,757 closed during the 15 years, and knowing that the average duration of a KAFALAT loan is around 5 years, this means that the volume of activities from 2010 to 2015 was considerably larger than the years 2000 to 2005. This has reflected a higher rate of default especially in 2011 (17.5%). This trend is normally observed as any other new businesses in the market that are still not very well known to banks and customers. It has taken time for banks to adapt to the procedures related to KAFALAT guaranteed loans.

Loan default risks decreases for banks that usually issue more KAFALAT loans than others (Madani, 2010). This is explained by the fact that banks learn how to better assess, treat and follow-up with SMEs loans files. This leads to better organize the bank's credit scoring process by becoming more familiar to the risks in the field while remaining consistent with their high standards and customer oriented practices. A bank that has the ideology of supporting the Lebanese SMEs by financing the new start-ups has the potential to increase their focus on KAFALAT guaranteed loans.

The average default rate of 18.58% for a mean duration of 5 years, implies that the annual risk in on average is 3.71%. The premium received by KAFALAT is 2.5% per year. Let us consider that this premium includes the risk of default and the operating cost (estimated 0.5% of the value of the loan), we can confirm that the premium received by KAFALAT is fair throughout the loan. This means that the directors of KAFALAT had a sustainable vision for this program by putting this premium. However, this is also due to the uncertainty of risks originating from the lack of historical data since the establishment of KAFALAT program in 1999. An update of the conditions and policy of risk scoring for SME's is needed to secure a fair lending by the program.

The different default rates facing sectors, geographic regions and borrowers require an urgent investigation on the validity and effectiveness of the current practices by applying a unified risk premium for all loans without taking into account their feasibility studies and specific characteristics.

The default rate which increases with the length of the loan, shows the complexity that occurs once an SME is given a loan. This proves the need for a deeper responsibility in management control.

Finally, we should emphasize that the empirical study failed to show a preference directly related to a particular sector. The Lebanese banks have adopted new positioning strategies to evaluate the risks of each sector. Likewise, KAFALAT program has introduced new loan preferences pertaining to energy loans and Trees loans, which would help evaluate the risks in these new areas of business.

CHAPTER V

CONCLUSION

A. Summary of results

The exploration of SMEs in a global and local perspective shows their importance to the Lebanese economy. However, issues in Small and Medium Enterprises access to finance are still common. The financing of SMEs through Banks that are available in Lebanon are still conditioned by taking collateral that the borrower often cannot provide, and always cautious about approving loans. That is where the SMEs loan guarantee programs intervenes; namely KAFALAT, coupled with the initiative by the Lebanese government to subsidize the cost of financing, to soften the supply and to stimulate the demand.

As for the theoretical part, we discussed and presented in general the approaches to credit risk assessment. We explained the limitation of the quantitative models based on financial information and its non-adaptability to the Lebanese context. Furthermore, we explored the principles and the credit approval criteria for SMEs, including hybrid systems, scoring and expert systems of which we explained their components. However, the important point to understand the weak points in the structure of SMEs has been explored in the empirical analysis of the performance of KAFALAT guarantee program in the last fifteen years. Through this analysis of SME loan defaults, we were able to understand several causal relationships between characteristics and performances. The empirical results can provide a reference tool of pricing for the loan guarantee, as well as the calibration of different criteria and parameters existing in analytical practices and scoring systems of SME loan applications. This approach, starting from the on-side observation, must interact with the already established assessment models. This feedback will benefit financial agents as well as credit officers to understand SMEs in Lebanese commercial banks.

The Lebanese agro-food sector is a promoter of job creation. Therefore, several opportunities reside within the sector, as the latter is almost immune to the local and regional uprisings. Moreover, great potential for development resides within the agro-food activity, yet more investments are needed to realize economies of scale, thus boosting productivity and increasing entrepreneurial projects.

The findings of this study open an interesting horizon to the update of the SMEs loan guarantee conditions set by KAFALAT. The foundations and economic estimates leading to the creation of KAFALAT are dated since the ends the 90s. Many factors have changed and several on-side data confirmed this. Several questions can be asked: Is it the time to adjust the premiums and guarantee coverage percentages according to the relative risk of each applicant? Is it true that once individual are listed into a capital stock company, it makes SMEs more organized and better able to cope with the different challenges that affect its sustainability?

B. Study Limitations

Since the analysis and comments are based on qualitative data (Business Type, sector, geographical area etc.), the results should be interpreted with caution. Therefore, it is necessary to disclose the drawbacks that we encountered in this study. The lack of information regarding the borrower's sex and age was major limitation. Thus, the role, contribution and the degree of risk associated with the role of younger or older borrowers, and women in SMEs cannot be addressed or quantified. Moreover, the study does not take into account multiple important existing variables that do exist in the original database but were not disclosed in our dataset of which:

A - The status whether it is a "New project" or an "Existing project". Therefore, no approach could determine if a new project has additional default chances in contrast to already existing projects. This would have introduced a refinement element in the Scoring

B - Bank Names and their locations, which would have helped us locate and determine the risks of loan defaults associated with the location of the banks relatively to the location of the project.

C - Defaulting occurrence date. This can help us determine if loan defaulting is time-dependent and that the factors affecting default behavior, as well as its timing, are maturity specific.

In addition, the analysis of the effect of interest rates assigned to loans for SMEs cannot be performed because the rates applied are predetermined and are not the same for all loans but it is based on exogenous conditions.

C. Suggestions for future studies

It would be interesting to integrate in future studies the debt recovery effect in previous years. In fact, KAFALAT made certain recovery operations on executed guarantees which information was not available at the time of preparation of this study. Entering and updating financial data of guaranteed SMEs by KAFALAT will incorporate more quantitative attributes and create opportunities for new analyzes (test the accuracy of the Z-Score for example), especially that the ASAIL is working with Byblos Bank on the development of feasibility templates to be used by Bank loan officers to facilitate the disbursement of agricultural loans. The analysis of the structure of the loan portfolio to SMEs in Lebanese banks should have more historical data to evaluate its performance and its evolution. Similar studies should incorporate a legal party to compare the effect of the legal framework for business on its performance. This variable was very important on the results provided by this study.

In conclusion, the logistic regression model allowed us to identify some qualitative aspects of the SMEs in Lebanon that may influence the credit situation of the latter and consequently its probability of default. These elements considered in a risk analysis system based on a borrower application analysis can provide additional information to the loan officer, to better assess the overall situation of an SME borrower within a Lebanese bank. The study opens a large question on the legal and political framework for businesses in Lebanon and shows the need for new legislation that ensure correct financial structure for enterprises, strength to their capital, and promotion to entrepreneurship.

As for the political context, it is obvious to say that political stability will ensure positive effects to the economy in general and to the businesses in particular. Political stability enables the establishment of additional investment projects, more businesses and encourage people to make long-term economic exchanges. More projects will default; however, more projects will succeed and be considered in the evolutionary cycle of companies. Therefore, long-term thinking should become an essential strategy for all the Lebanese entrepreneurs, which, sadly, is so far lacking in Lebanon.

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APPENDIXES

Figure 2 Main Financial Credit Ratings

Principales notations financières

Moody's		Standard & Poor's		Fitch Ratings		Commentaire
Long terme	**Court terme**	**Long terme**	**Court terme**	**Long Terme**	**Court terme**	
Aaa	P-1	AAA	A-1+	AAA	F1+	*Prime*. Sécurité maximale.
Aa1		AA+		AA+		*High Grade*. Qualité haute ou bonne.
Aa2		AA		AA		
Aa3		AA-		AA-		
A1		A+	A-1	A+	F1	*Upper Medium Grade*. Qualité moyenne.
A2		A		A		
A3	P-2	A-	A-2	A-	F2	
Baa1		BBB+		BBB+		*Lower Medium Grade*. Qualité moyenne inférieure.
Baa2	P-3	BBB	A-3	BBB	F3	
Baa3		BBB-		BBB-		
Ba1	*Not Prime*	BB+	B	BB+	B	*Non Investment Grade*. Spéculatif.
Ba2		BB		BB		
Ba3		BB-		BB-		
B1		B+		B+		Hautement spéculatif.
B2		B		B		
B3		B-		B-		
Caa		CCC+	C	CCC	C	Risque substantiel. En mauvaise condition.
Ca		CCC				Extrêmement spéculatif.
C		CCC-				Peut être en défaut.

Information Value (IV)

An important analysis in logistic regression is the information value. It shows how valuable is the variable in question to classify defaulted and successful loans. Due to the obtained Odds ratios, I have calculated the IV for each category. After that, I calculated the total IV for each variable by summing up all the Category values. We define the Information Value by

$$IV = \ln(Odds) * \left(\frac{Defaulted_i}{Defaulted}\right) - \left(\frac{non{-}Defaulted_i}{non{-}Defaulted}\right)$$

This gives us the predictive power of each variable in our model. If the information value of a certain category is high, therefore its predictive power is high as well. We will be using the IV to choose which variables have the highest predictive power to include in our analysis. An IV value of 0.2 in banking practice is considered a sign of strong predictability of a variable (Kocenda and Vojtek, 2009). However, our IVs are all high. The Information values for the all the categories of variables can be found in the Appendix table 1.

Table 8 Information Value for Variables

Sectors	Closed	Default	Grand Total	Response Rate	Closed %	Defaulted %	Population	IV
Agriculture	2095	374	2469	15.1%	38.1%	29.8%	36.5%	0.02028
Crafts	172	34	206	16.5%	3.1%	2.7%	3.0%	0.00060
Industry	2415	500	2915	17.2%	43.9%	39.8%	43.1%	0.00393
Technology	117	24	141	17.0%	2.1%	1.9%	2.1%	0.00023
Tourism	703	323	1026	31.5%	12.8%	25.7%	15.2%	0.09075
Grand Total	5502	1255	6757	19%	100%			0.11579

Regions	Closed	Default	Grand Total	Response Rate	Closed %	Defaulted %	Population #	IV
Beirut	386	129	515	15.1%	7.0%	10.3%	7.6%	0.01246
Bekaa	996	177	1173	16.5%	18.1%	14.1%	17.4%	0.00998
Mount Lebanon	2583	614	3197	17.2%	46.9%	48.9%	47.3%	0.00082
Nabatieh	185	29	214	17.0%	3.4%	2.3%	3.2%	0.00394

North	590	192	782	31.5%	10.7%	15.3%	11.6%	0.01626
South	762	114	876	31.5%	13.8%	9.1%	13.0%	0.02010
Grand Total	5502	1255	675700%	1.287895857	100%			0.06357

Borrower Type	Closed	Default	Grand Total	Response Rate	Closed %	Defaulted %	Population #	IV
Company	2019	640	2659	24.1%	36.7%	51.0%	39.4%	0.04706
Individual	3008	557	3565	15.6%	54.7%	44.4%	52.8%	0.02145
Partnership	475	58	533	10.9%	8.6%	4.6%	7.9%	0.02507
Grand Total	5502	1255	675700%	0.185733314	100%	1	1	0.09358

Guarantee Rates	Closed	Default	Grand Total	Response Rate	Closed %	Defaulted %	Population #	IV
70	67	73	140	52.1%	1.2%	5.8%	2.1%	0.07192
75	5015	765	5780	13.2%	91.1%	61.0%	85.5%	0.12148
85	412	402	814	49.4%	7.5%	32.0%	12.0%	0.35672
90	8	15	23	65.2%	0.1%	1.2%	0.3%	0.02212

Grand Total	5502	1255	675700%		100%	1	1	0.57223

Program	Closed	Default	Grand Total	Response Rate	Closed %	Defaulted %	Population #	IV
Basic	5079	838	5917	14.2%	92.3%	66.8%	87.6%	0.08271
Innovative	9	16	25	64.0%	0.2%	1.3%	0.4%	0.02282
Plus	410	400	810	49.4%	7.5%	31.9%	12.0%	0.35490
Small Farmers	1	1	2	50.0%	0.0%	0.1%	0.0%	0.00091
Trees	3	1	3	33.3%	0.1%	0.1%	0.0%	0.00010
Grand Total	5502	1255	675700%		100%	1	1	0.46144

Table 9 Model 2 All Variables including Grace Period and Interest Rate

	Coef	SE	Odds	P.v	95% CI	
Loan Period						
Agriculture	0.051	0.005	10.590	0.000	0.042	0.061
Crafts	0.064	0.019	3.360	0.001	0.027	0.101
Industry	0.054	0.005	11.700	0.000	0.045	0.063
Technology	0.026	0.018	1.470	0.141	-0.009	0.061
Tourism	0.043	0.006	6.880	0.000	0.030	0.055
85% & 90% Program						
Agriculture	-1.585	0.318	-4.980	0.000	-2.209	-0.961
Crafts	-2.722	1.004	-2.710	0.007	-4.690	-0.755
Industry	-1.634	0.135	-12.120	0.000	-1.899	-1.370
Technology	-3.698	0.883	-4.190	0.000	-5.429	-1.967
Tourism	-2.187	0.194	-11.300	0.000	-2.567	-1.808
Beirut & Mt Lebanon						
Agriculture	0.291	0.133	2.180	0.029	0.030	0.552
Crafts	0.842	0.439	1.920	0.055	-0.019	1.702
Industry	-0.096	0.119	-0.810	0.418	-0.330	0.137
Technology	0.772	0.821	0.940	0.347	-0.838	2.381
Tourism	-0.487	0.198	-2.460	0.014	-0.874	-0.099
Sole Proprietorship						
Agriculture	0.350	0.183	1.920	0.055	-0.008	0.709
Crafts	0.140	0.536	0.260	0.794	-0.911	1.191
Industry	0.375	0.131	2.870	0.004	0.119	0.632
Technology	0.841	1.343	0.630	0.531	-1.791	3.473
Tourism	0.576	0.202	2.850	0.004	0.180	0.973
Interest Rate						
Agriculture	-0.030	0.020	-1.550	0.121	-0.069	0.008
Crafts	0.089	0.077	1.160	0.247	-0.062	0.241
Industry	-0.019	0.020	-0.960	0.339	-0.057	0.020
Technology	0.089	0.122	0.730	0.464	-0.150	0.328
Tourism	0.016	0.031	0.520	0.601	-0.044	0.077

Grace Period						
Agriculture	-0.002	0.017	-0.100	0.918	-0.035	0.032
Crafts	0.002	0.071	0.020	0.982	-0.138	0.141
Industry	-0.019	0.017	-1.110	0.266	-0.052	0.014
Technology	0.010	0.097	0.100	0.921	-0.180	0.200
Tourism	0.004	0.026	0.150	0.881	-0.046	0.054
Sectors						
Agriculture	-0.938	0.286	-3.280	0.001	-1.498	- 0.377
Crafts	0.196	0.903	0.220	0.828	-1.574	1.966
Industry	-0.602	0.112	-5.390	0.000	-0.821	- 0.383
Technology	-0.062	0.462	-0.140	0.893	-0.968	0.843
Tourism	0.321	0.143	2.240	0.025	0.040	0.602

Table 10 Probability of Default Scenarios for All Sectors under 30 Months

	At loan period (30 months)							
	Partnership and Company				Sole Proprietorship			
	85-90% Guranatee level				70-75% Guranatee level			
	Beirut & ML		Beqaa, North & South		Beirut & ML		Beqaa, North & South	
	Odds	Pr	Odds	Pr	Odds	Pr	Odds	Pr
Agriculture	0.10	8.81%	0.07	6.72%	0.01	1.40%	0.01	1.05%
Crafts	0.30	23.19%	0.14	12.10%	0.02	1.49%	0.01	0.68%
Industry	0.09	8.06%	0.10	8.79%	0.01	1.14%	0.01	1.25%
Technology	0.53	34.76%	0.19	15.94%	0.03	3.38%	0.01	1.23%
Tourism	0.19	16.20%	0.29	22.51%	0.02	2.10%	0.03	3.12%

Table 11 Probability of Default Scenarios for All Sectors under 73 Months

	At mean loan period (73 months)							
	Partnership and Company				Sole Proprietorship			
	85-90% Guranatee level				70-75% Guranatee level			
	Beirut & ML		Beqaa, North & South		Beirut & ML		Beqaa, North & South	
	Odds	Pr	Odds	Pr	Odds	Pr	Odds	Pr
Agriculture	0.73	42.33%	0.55	35.38%	0.11	9.75%	0.08	7.46%
Crafts	3.48	77.67%	1.59	61.33%	0.17	14.82%	0.08	7.35%
Industry	0.72	41.83%	0.79	44.14%	0.09	8.65%	0.10	9.42%
Technology	1.61	61.66%	0.57	36.40%	0.11	9.55%	0.04	3.62%
Tourism	1.08	51.97%	1.63	61.92%	0.12	10.72%	0.18	15.29%

Table 12 Probability of Default Scenarios for All Sectors under 85 Months

	At loan period (85 months)							
	Partnership and Company				Sole Proprietorship			
	85-90% Guranatee level				70-75% Guranatee level			
	Beirut & ML		Beqaa, North & South		Beirut & ML		Beqaa, North & South	
	Odds	Pr	Odds	Pr	Odds	Pr	Odds	Pr
Agriculture	1.35	57.42%	1.01	50.15%	0.68	40.57%	0.92	47.89%
Crafts	7.24	87.86%	3.30	76.75%	2.24	69.11%	5.07	83.53%
Industry	1.35	57.47%	1.49	59.76%	0.74	42.63%	0.75	42.82%
Technology	2.24	69.13%	0.80	44.36%	0.07	6.67%	0.19	15.83%
Tourism	1.81	64.46%	2.73	73.16%	0.78	43.72%	0.54	35.09%