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Determining the Probability of Default of Agricultural Loans in a French Bank

Amelie Jouault[1] and Allen M. Featherstone[2]

Abstract

Recently, financial institutions have developed improved internal risk rating systems and emphasized the probability of default and loss given default. The default characteristics are studied for 756 loans from a French bank: CIC- Banque SNVB. A binomial logit regression is used to estimate several models of the probability of default of agribusiness loans based on information available at loan origination. The results show that leverage, profitability and liquidity at loan origination are statistically significant indicators of the probability of default. As leverage increases, profitability decreases, or liquidity decreases, the probability of default increases. As the length of loan increases, the probability of default also increases. Finally, it is more accurate to develop a model for each type of collateral (activity). By developing more quantitative credit scoring models, banks may benefit from lower capital requirements while borrowers may see better rates where the risk of loans is appropriately priced.

JEL classification numbers: Q14 G21

Keywords: Agricultural credit risk, probability of default, agribusiness loan, French banking

[1] Latin American Agribusiness Development, e-mail: ameliejouault@hotmail.com
[2] Kansas State University, e-mail: afeather@ksu.edu

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1 Introduction

As the New Basel Capital Accord encourages financial institutions to develop and strengthen risk management systems, banks are interested in obtaining a more objective rating of loan portfolios. High levels of indebtedness imply a higher incident of default and increasing risk for lenders. Because agricultural credit conditions change rapidly, the adoption of technology in the sector has caused the shifting of production risk to financial risk [20].

Quantifying financial risks and developing an effective portfolio management strategy are important objectives of banks. Banks consequently devote many resources to developing internal risk models. Financial risk can be divided into credit, market and operational risk but the largest component is credit risk [9]. By developing an accurate credit risk rating system, banks will be able to identify loans that have lower probability of default versus loans that have a higher probability of default. Thus, they will better rate the loans and ultimately price the loans.

In this study, we focus on a French bank that serves agriculture: Crédit Industriel et Commercial- Société Nancéienne Varin-Bernier (CIC-Banque SNVB). Much of the literature on default risk has been performed using U.S. financial institutions whose accounting systems differ from other countries. After analyzing the differences in financial reporting methods and credit scoring approaches between the U.S. and France, we examined financial ratios that are important for evaluating the probability of default. We also examine whether the length of the loan and the commitment amount are significant predictors of the probability of default of a loan. Finally, we examine whether a model for each type of farming activity or a single model should be developed.

2 Financial reporting practice and credit scoring in France

2.1 Financial reporting practice

Previous research has identified a dichotomy in accounting systems around the world: the Anglo-American model versus the Continental European model. Major differences exist between these two types of accounting models in terms of valuation and presentation methods [15]. In the Anglo-American model, financial statements include a balance sheet, income statement, statement showing changes in equity, cash flow statement, accounting policies and explanatory notes. The European model requires a balance sheet, profit and loss account and notes on the accounts. The number of periods disclosed is another difference. American companies usually disclose two or three years' figures whereas in France only one comparative period is usually disclosed.

Furthermore, in France as in the United States, the balance sheet is usually presented horizontally with two blocks side by side. Nevertheless, there is a difference in the classification of assets and liabilities. French accounting gives a priority to the classification by nature. In the United States, items in the balance sheet are presented in order of decreasing liquidity and maturity. Fixed assets are shown in three columns in France: gross value, accumulated depreciation and net value while often only the net value is reported in the U.S. The valuation of assets in the farm sector differs in that assets are valued on a cost-basis in France while they are at adjusted market-value in the U.S. For example, the asset value of a vineyard bought 30 years ago is its costs 30 years ago in France. In the U.S., the asset value of this vineyard is its market value so its asset value is much higher than the one appearing in the French balance sheet.

As far as the income statement is concerned, the most traditional format used in France is the nature of expense method; expenses are aggregated according to their nature: transport, tax or salaries for example. The United States adopts the function of expense method; expenses are classified according to their purpose: commercial, distribution, etc. [16].

2.2 Explanations for differences in financial reporting practice

Several researchers examined the factors that influence the differences in national accounting standards. Nobes [14] defined two accounting-system categories: micro-based (the U.S.) versus macro-based (France). Micro-based systems are complex, less conservative and present higher disclosure than macro-based ones. According to Doupnik and Salter [2], the legal system is another explanation. The U.S. has a common-law heritage, which generally is less rigid and allows for more discretion in application than code-based law traditions (France). The source of financing, according to Zysman [22], explains the gap as well. The U.S. has a capital market based system, so shareholders do not necessarily have privileged relationship with companies, which is why public disclosure of financial information is required. France has a credit-based system. Radebaugh and Gray [18] indicate that the government is the major source of financing in France and it has strong relationships with companies. Therefore, companies are concerned with the protection of creditors and the calculation of distributable profit. Hofstede's uncertainty avoidance dimension is also linked to the differences in accounting standards of the two countries [8]. The uncertainty avoidance dimension measures how people feel towards ambiguity. France, contrary to the U.S., ranks high on uncertainty avoidance which means that they prefer formal rules.

2.3 Credit scoring approach of CIC

In France, each bank builds its own credit risk rating system. The French group CIC segmented its clientele into 8 markets and developed a specific credit scoring model for each market. The agricultural segment, one of those 8 segments, used two separate models to assign a score to a loan application that is a combination of two grades.

The first model is based on ratios obtained from the balance sheet while the second model is based on the way the farm operates. In the first model, the ratios are:

- total equity /financial debt (r1)
- other debt /current assets (r2)
- bank interest/operating profit before depreciation and amortization (r3)
- cash balance*365/cost of goods sold (r4).

It should be noted that each of the first 3 ratios are in some respects measures of leverage, where the fourth measure is a measure of liquidity. The second model uses six criteria to assign the second grade:

- a risk indicator (r5)
- monthly average of creditor balance over the past year (r6)
- number of days over the allowed spending limit during the past year (r7)
- monthly average balance on checking account (r8)
- three months average debtor balance over average creditor balance (r9)
- total savings of the borrower (personal and professional accounts), (r10)

The algorithms showing the calculation of the two grades are provided in table 1. The two grades obtained from the two models are aggregated to calculate a total score used to categorize the loan applications into 9 risk classes as shown in table 2.

This new scoring model was implemented in 2003 so all the information necessary to calculate the score was not available in the bank's historical data information system. Prior to the implementation of this loan scoring model, approval relied on the subjective judgment of the lender who analyzed the borrower's financial position, evaluated the firm's management and previous repayment histories. Besides the financial ratios evaluated with the scoring model, there are other factors that can only be evaluated by the lender: the family situation, the farmer's management expertise or non farm activities.

3 Background

3.1 Definition and purpose of credit risk rating systems

Lopez and Saidenberg [13] define credit risk as the degree of value fluctuations in debt instruments and derivatives due to changes in the underlying credit quality of borrowers. They identify two main concepts of credit risk that differ in the definition of credit losses. Default models focus on the probability of default, while mark-to-market or multi-state models evaluate how changes in rating class affect the loan market value.

Credit-scoring models examine the creditworthiness of customers by assigning them to various risk groups. These models provide predictions of default probabilities using statistical classification techniques. The purpose of credit-scoring models is to assist the risk evaluation and management process of individual customers and loan portfolios. Credit-scoring tools are necessary to assist the loan officer in making loan decisions, controlling and monitoring loan portfolio risk and isolating loans that need additional attention [17]. The fundamental goal of a credit risk rating system is to estimate the risk of a given transaction. The "building block " for quantifying credit risk is Expected Loss (EL), the loss that can be expected from holding an asset. This is calculated as the product of three components: the probability of default (PD), the loss given default (LGD), and the exposure at default (EAD). EL is defined as:

$$EL = PD*LGD*EAD \tag{1}$$

The probability of default (PD) is defined as the frequency that a loan will default and is expressed in percentage terms. The loss given default (LGD) measures the cost for the financial institution when the loan defaults. It is expressed in percentage terms. The exposure at default (EAD) is the amount of money outstanding when the default occurs. The ultimate goal is to provide a measure of the loss expected for a credit and the capital required to support it. Most rating systems use a two-dimensional scale to solve this problem, with the probability of default and the loss given default being quantified separately [21].

Czuszak [1] confirms the importance of the probability of default stating that credit risk measurement and management is found in the probability and financial consequences of obligator default. Gustafson, Pederson and Gloy [11] list the numerous costs involved when default occurs. Featherstone and Boessen [4] studied loan loss severity in agriculture and computed the expected loss by multiplying by EAD and LGD. Katchova and Barry [12] utilize the three components, PD, EAD and LGD, to model the expected loss encountered when default occurs.

3.2 Approaches of credit risk evaluation

Gustafson, Beyer and Barry [10] defined two types of approaches to credit risk assessment: the transactional approach which focuses on credit risk assessment tools, and the relational approach which in addition to credit scoring models, relies on the relationship between lenders and borrowers so as to evaluate others factors such as management capacity. The CIC Banque SNVB credit scoring approach uses the second approach. The traditional approach to agricultural lending relies on the relationship between the loan officer and the borrower. This relationship allows for a reduction in asymmetric information between borrower and lender that arises from the fact that borrowers are familiar with their business, financial position and repayment intentions, and those characteristics are not easily observable by lenders. The other approach, transactional, places a greater reliance on financial ratios and places less focus on a relationship. While the goal of a risk rating system is to produce accurate and consistent ratings, professional judgment and experience are allowed as a part of the rating process. Judgmental rating systems are more costly but the benefits may outweigh the costs for larger banks.

To measure the accuracy of risk rating systems that employ both judgmental and statistical analysis, Splett et al. [19] created a joint experience and statistical approach of credit scoring.The results from the experience were used as dependent variables in a logit regression model. The results indicated relatively high success of the statistical model in replicating the ratings from the experience model.

Featherstone et al. [16] evaluated the factors affecting the loan decision process by evaluating lenders response to hypothetical loans in Kansas and Indiana. These loans differed by a borrower's character, financial record keeping skills, production management skills, Fair Isaac credit bureau scores, and credit risk. Results found that financial condition and character are both important in the loan evaluation process and these factors are important in the interest rate decision.

3.3 Credit risk rating models

Ellinger, Splett and Barry [3] surveyed lenders to determine the use of credit evaluation procedures. They found that 62% of respondents used a credit scoring model to assist in loan approval, loan pricing and loan monitoring. This proportion increased with bank size.

Most of the actual credit rating systems rely on financial ratios but some research has been extended to nonfinancial ratios. Stover, Teas and Gardner [20] extended the loan decision to loan pricing, collateral and changing market conditions. The decision variables for the loan were character and ability of management, the conditions of the agricultural market, compliance with the bank's loan policy, collateral and loan pricing. To test these variables, 44 agricultural lending officers were asked to sort hypothetical loans from the most preferred loan to the least preferred one. OLS regression was used to estimate the aggregate utility model. The results confirm the important role of management ability and character of the borrower.

Gallagher [7] looked at nonfinancial characteristics between unsuccessful and successful loans by including a combined experience variable comprised of the loan officer's experience and the agribusiness manager's experience. The model prediction success rate went from 80% to 97.5% with the inclusion of this information.

4 Data

Data were provided by CIC Banque SNVB, bank located in north-eastern France (figure 1). CIC is a French bank group which is comprised of 9 regional banks, CIC Banque SNVB is one of them. CIC joined the Crédit Mutuel in 1998 and today, the Crédit Mutuel-CIC group is the 4th largest bank group in France. At the end of 2003, CIC Banque SNVB's net income was 341 million Euros with about 2,500 employees working for it.

CIC Banque SNVB has targeted the agricultural market because this region is one of the most efficient regions in agricultural and wine production: the Marne, Seine et Marne and Aube. The potential CIC Banque SNVB territory is 46,000 farms, where the chief activities are crops, milk and wine production. This bank targets diversified farms whose sales are greater than 150,000 Euros. More than 2,500 farmers were customers of the CIC Banque SNVB as of October 30, 2004. The typology of the clientele is depicted in figure 2. The activities of the customers are diverse; the main activities are wine production and crops, which represents 27% and 20% of the clientele, respectively.

The loan data obtained from the CIC Banque SNVB were loans that originated between January 1, 1999 and May 31, 2004. The data were categorized by customer level and loan level. The customer level data corresponds mainly to the financial situation of the customer every year. A customer may be in the dataset more than once because information is entered each year. Even though financial statements are added through the years, the financial statements from origination are saved. This study focuses on the origination data. The customer level data are the customer ID, year of the financial data, total equity, level of participation of a partner if applicable, long-term debt, short-term debt, working capital, cash balance, total assets, total equity and liabilities, sales, operating profit before depreciation and amortization, bank interest, intermediate income and net income. The loan level data are updated at least every year or once a major event affects the quality of the loan. The data reflects the quality (default or non-default) of the loans as of May 31, 2004. The loan level data contain customer ID, date of origination, date of maturity, code of loan and description, commitment amount, length, amount due that has been borrowed, type of collateral, indicators of default: payment past due 90 days or increase of the provision for loan loss, frequency of payment and dominant activity of the business. The data are aggregated so the loan information is linked to the customer financial data available at origination.

The original data contained 2,600 agricultural loans booked between 1999 and 2004. The customer data were linked to the loan to match the year of origination with financial information from the previous year. Some information was lost because complete financial information was not available for all loans. Among the 756 remaining loans, 6.35% of the loans defaulted.

5 Methods

Binomial logit regression is used to estimate a model predictive of the probability of default (PD) of an agribusiness loan and identify the significant components of non-defaulted loans.

5.1 Model I

The first model is based on origination financial ratios used by the credit scoring model of CIC-Banque SNVB. Model I is as follows:

$$ln([PD]_I/1-[PD]_i) = \beta_0 + \beta_1 \; leverage_{1i} + \beta_2 \; other \; leverage_i + \beta_3 \; coverage_i + u_i \quad (2)$$

where *i* refers to the loan and *u* to the error term.

5.2 Model II

An alternative model is specified using origination rations that have been found in studies of the U.S. agricultural credit market to affect the expected probability of default (PD) of a loan:

$$ln(PD_i /[1\text{-}PD)]) = \beta_0 + \beta_1 \, leverage_{2i} + \beta_2 \, profitability_i + \beta_3 \, liquidity_i + u_i \qquad (3)$$

where *i* refers to the loan and *u* to the error term.

5.3 Variables description

5.3.1 Dependent variable

The dependent variable of both models is log odds ratio of *default.* This binary variable takes the value 1 if the loan defaulted and 0 otherwise. Default is defined as a loan that has not been repaid at least once within 90 days or more since the payment was due.

5.3.2 Independent variables in model I

In model I, the first ratio, $leverage_1$, is measured as total equity over financial debt. Financial debt is defined as all the debt to financial institution. The higher the amount of equity compared to the amount of debt, the lower the risk of default; thus the sign of this coefficient is expected to be negative. The definition of the second ratio, *other leverage*, is other debt over current assets. Other debt corresponds to short-term debt to suppliers, tax and social benefit creditors. The higher the amount of short-term debt, the lower the repayment capacity, thus the risk of default is higher. The last ratio utilized in model I is a measure of *coverage*, which is defined as bank interest over operating profit before depreciation and amortization. The higher the amount of debt, the higher the amount of bank interest, thus the coefficient on this ratio is expected to be positive. Also, if profit is lower, the ratio is higher, and the probability of default is lower.

5.3.3 Independent variables in model II

Three origination variables are included in model II: leverage, profitability and liquidity. $Leverage_2$ corresponds to debt ratio and is defined as total liabilities divided by total assets. This definition differs from the measure of leverage above that only considers debt to the financial institution. The debt ratio shows the proportion of a company's assets that are financed through debt. In addition, this measure of leverage takes into account the total leverage picture as opposed to considering leverage in subcomponents as modeled above. Firms with a high debt ratio are said to be "highly leveraged," and are more likely to default. Therefore, the sign of the coefficient is expected to be positive. The *profitability* variable is defined as the rate of return on assets, which equals the fiscal year's net income plus interest divided by the total assets of the company. It is expressed as a decimal in this study. The coefficient of this variable is expected to be negative since higher profitability should result in a smaller risk of default. It should be noted that the CIC model discussed above does not have a direct measure of profitability that can ultimately lead to repayment ability. *Liquidity* is defined as working capital and equals current assets minus current liabilities. This number can be positive or negative. Companies that have more working capital may be more successful since they can expand quickly with internal resources. Companies with low working capital may lack the funds necessary for growth. This variable is expressed in Euros.

Two other variables are also investigated that have been found to affect the probability of default in previous studies: the length of the loan and the commitment amount. The *length* of the loan is computed by calculating the number of months between the origination date and the maturity date of the loan. The intuition for the expected sign is that the longer the loan, the lower the amount of principal repaid, the higher the risk of default. The *commitment amount* variable represents the amount of principal that has been approved and booked.

Featherstone et. al. [5] found that loan size does not significantly influence whether or not a loan will enter default status.

A final objective of the study is to examine whether farm type is related to the probability of default. The sample obtained from the CIC-Banque SNVB is classified into four types as shown in table 3: agriculture, wine and champagne production, agricultural services and others.

5.4 Summary statistics

The summary statistics are provided in table 4 and table 5. There were 756 loans approved of which 48 defaulted, leading to a default percentage of 6.35%. Table 4 summarizes the variables for model I. The mean for leverage is higher for the non-defaulted loans than the defaulted loans. For other leverage, the mean is higher for defaulted loans. Also, the mean for coverage is higher for defaulted loans.

Table 5 corresponds to the variables used in model II. Leverage has a smaller coefficient of variation than profitability and liquidity. The length of the loan varies from 6 months to 20 years. The mean for leverage is higher for the defaulted loans than the non-defaulted loans as expected. Profitability for both defaulted and non-defaulted loans is similar. Liquidity is higher for non-defaulted loans. The mean loan length is 64.73 months for non-defaulted loans and 76.83 for defaulted loans. Finally, non-defaulted loans have a higher commitment amount than defaulted ones.

6 Regression Results

6.1 Probability of default results: Model I

Model I utilized three of the origination ratios included in the CIC credit scoring model: leverage, other leverage and coverage. The binary logit regression results are presented in Table 6. The signs obtained for the coefficients are as expected. Nevertheless, the chi-square statistic indicated that none of the variables are statistically significant at the 95% confidence level. The likelihood ratio test (1.62), distributed as a chi-square distribution, indicates that the null hypothesis (β_i=0 for all variables) cannot be rejected. The model is not statistically significant in predicting the probability of default.

6.2 Probability of default results: Model II

Model II utilizes three independent variables: leverage, profitability and liquidity. The results of the regression are displayed in Table 7. The chi-square statistic indicated that all the variables are statistically significant at the 95% confidence level. The coefficient for leverage is positive and the coefficients for profitability and liquidity are negative. The result of the likelihood ratio test (18.17), distributed as a chi-square distribution, indicates that the null hypothesis, β_i=0 for all variables, is rejected. The model is statistically significant in predicting the probability of default.

To interpret the economic content of the coefficients, further computations need to be made. For a binary logit model, the impact of a one-unit increase of the independent variable, other explanatory variables held constant, is not the probability of default itself. The probability of default (P_i) is given by:

$$P_i = \exp(\beta_0 + \sum \beta_j x_{ij}) / (1 + \exp(\beta_0 + \sum \beta_j x_{ij})) \tag{4}$$

To estimate the marginal effect on the probability of default of one variable when the two others are held constant, the means for two of the variables were multiplied by their coefficients while one of the variables multiplied by the coefficient was varied. The marginal effect is evaluated between one standard deviation below and above the mean of the variable of interest.

Figure 3 represents the probability of default as the variables vary. Only model II was graphed because Model I was not statistically significant in predicting the probability of default. As leverage increases from .20 to 1, while the profitability and the liquidity are held constant, the probability of default increases from 2.33% to 4.73%. As the profitability increases from -0.8 to 1.2, the probability of default decreases from 6.05% to 2.47%. As liquidity increases from -100,000 to 200,000 Euros, the probability of default decreases from 8.9% to 5.3%.

6.3 Effects of the length of the loan on the probability of default

The length of the loan was examined to determine if longer loans have higher probability of default by adding loan length to model II. Similarly, the results indicate that all the origination ratios are statistically significant at the 95% level and have the expected signs (Table 8). The length of the loan is statistically significant in predicting the probability of default of loans; the longer the loan length is, the higher the probability of default.

6.4 Effects of commitment amount on the probability of default

Model II was re-estimated with commitment amount added. Each origination ratio is statistically significant at the 95% level and their signs are as expected (table 9). The coefficient estimate of commitment amount is not statistically different from zero, thus loan size does not have a statistically significant impact on whether a loan will enter default status. This is similar to the findings of Featherstone, Roessler and Barry [22].

6.5 Loan Type Results

The loans are further analyzed according to collateral type. Those activities are agriculture, wine production, services and others. For each type of activity, the independent variables from model II were regressed on the default outcome. For the agricultural model, all the signs obtained are as expected but only the working capital variable is statistically significant at the 95% level (table 10). The overall model is statistically significant in predicting the probability of default of loans as indicated by the likelihood ratio chi-square. The statistics of the wine production and agricultural services models indicate that neither the independent variables nor the overall model are good indicators of the probability of default of loans. The last category of other activities is mainly composed of hunting, forestry and fishing oriented businesses. All the coefficients of the independent variables have the expected signs and are statistically significant in predicting the probability of default of loans except the working capital variable.

To determine if it would be beneficial to implement a different model for each type of activity, we use a likelihood ratio test. The log likelihood statistics of the four categories are summed and subtracted from the log likelihood statistic of model II. The difference is distributed as a chi-square statistic; the number of degrees of freedom equals the number of sub-samples minus 1 times the number of parameters estimated. The result of the likelihood ratio test (30.82) indicates that we can reject the null hypothesis that the coefficient estimates are equal across loan type.

7 Conclusion

Three of the ten indicators utilized by CIC Banque SNVB to evaluate the credit risk were tested to determine their significance in predicting credit default. Those three origination ratios were leverage, other leverage and coverage. Those variables alone were not statistically significant in predicting whether a loan would default.

Three other origination variables that have been commonly used in other default studies were found to be important predictors of probability of default of the loans from the CIC Banque SNVB portfolio: leverage, profitability and liquidity. The commitment amount was not statistically significant while the loan length was statistically significant in predicting the probability of default. Differences exist between default models based on the type of farming activity. Thus, it is preferential to develop a model for each type of activity though this requires more data to estimate. By developing more quantitative credit scoring models, banks may benefit from lower capital requirements and lender will also better rate and price the risk.

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Table 1: Algorithm for Grade Calculations

Financial Model		Operating Model	
If $0 \leq r1 \leq 0.15$	then s1=-2.2798	If r5=0	then s5=-5.6846
If $0.15 < r1 \leq 0.50$	then s1=-1.3921	If r5=1	then s5=-2.0269
If $0.50 < r1 \leq 1.20$	then s1=-2.0102	If not s5=0	
If r1>1.20	then s1=-1.5840		
If not s1=0			
If $0 \leq r2 \leq 55$	then s3=1.6411	If $r6 \leq 0$	then s6=0.9057
If $55 < r2 \leq 85$	then s2=-1.1253	If $50 < r6 \leq 150$	then s6=0.6436
If $85 < r2 \leq 120$	then s2=-0.6771	If not s6=0	
If not s2=0			
If $-9999 \leq r3 \leq -105$	then s3=1.6411	If $0 < r7 \leq 3$	then s7=-2.6316
If $-105 < r3 \leq -60$	then s3=1.5291	If $3 < r7 \leq 9$	then s7=-1.9076
If $-60 < r3 \leq 0$	then s3=1.7963	If not s7=0	
If not s3=0			
If $0 \leq r4 \leq 0.12$	then s4=-1.8159	If $r8 \leq -4500$	then s8=1.4607
If $0.12 < r4 \leq 0.18$	then s4=-0.9122	If $-4500 < r8 < 0$	then s8=0.7160
If not s4=0		If not s8=0	
Fcalc = 1.5736+s1+s2+s3+s4		If $r9 \leq 0$	then s9=-0.9507
		If $0 < r9 \leq 0.05$	then s9=-0.8818
		If not s9=0	
F. Grade= 1/(1+exp(-Fcalc)		If $r10 \leq 150$	then s10=1.4420
		If r10>15500	then s10=-0.5451
		If not s10=0	
		Ocalc = 3.1967+s5+s6+s7+s8+s9+s10	
		O. Grade= 1/(1+exp(-Ocalc)	

Table 2: Calculation of the Score

If F. Grade >0 then score= $\sqrt{F.Grade * O.Grade}$

If not, Score= O. Grade

Risk Class	Score	% default[a]
1	≤ 0.04	0.10%
2	>0.04 and ≤ 0.09	0.22%
3	>0.09 and ≤ 0.18	0.68%
4	>0.18 and ≤ 0.31	0.94%
5	>0.31 and ≤ 0.45	2.48%
6	>0.45 and ≤ 0.60	3.51%
7	>0.60 and ≤ 0.75	6.80%
8	>0.75 and ≤ 0.90	12.29%
9	> 0.90	23.33%

[a] According to the study led by the bank to develop this credit scoring model
Source: Coisnon 2004

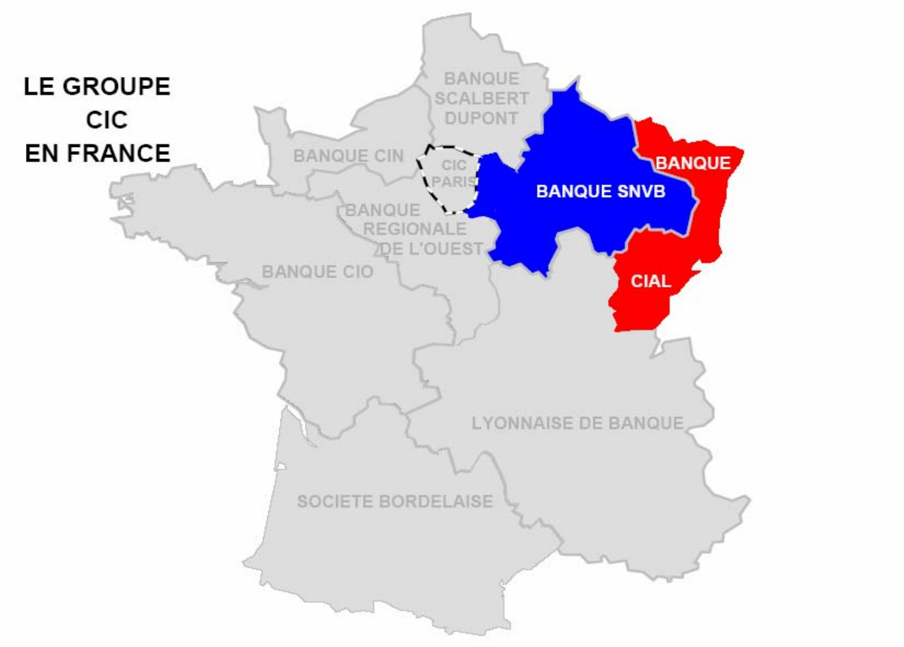

Figure 1: CIC group

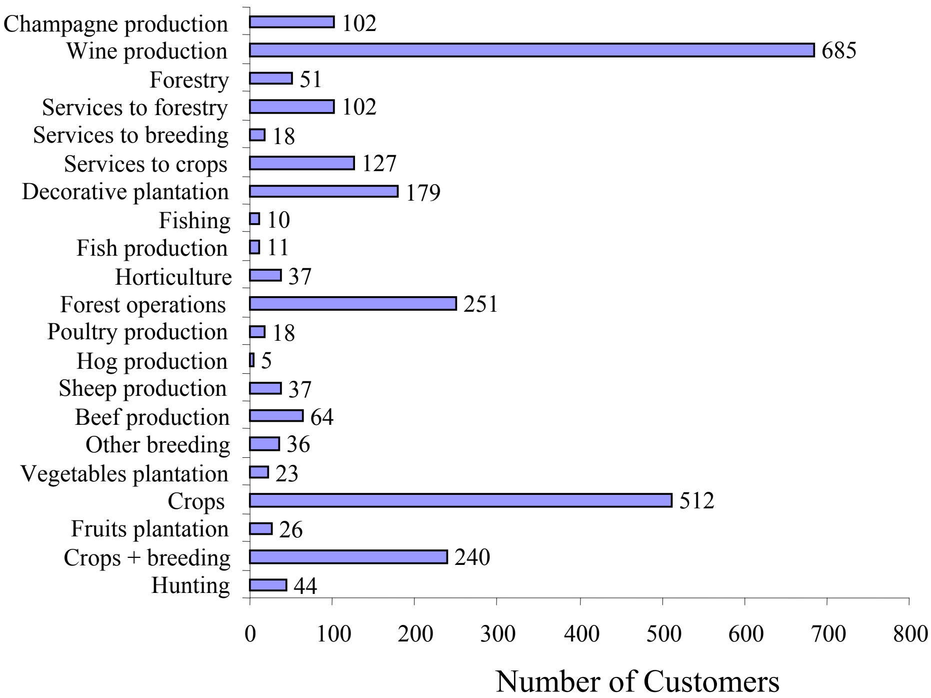

Figure 2: CIC Banque SNVB as October 2004 by farm type

Table 3: Description of the different type of activities

Type	*Description of the activity*
Agriculture (AG)	Crops
	Vegetables plantation
	Horticulture
	Fruits plantation
	Beef production
	Sheep production
	Hog production
	Poultry
	Others
	Crops + breeding
Wine production (WP)	Wine production
	Champagne production
Agricultural services (AS)	Services to crops
	Decorative plantations
	Services to stock farming
Other (Oth)	Hunting
	Forestry
	Fishing and fish production

Table 4: Descriptive Statistics CIC Banque SNVB, Model I variables

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
		All loans		
Leverage	7.3899	60.86518	-71.5	896
Other leverage	.7698	2.506706	-14.681	62.5
Coverage	.09767	1.8926	-32.3	12.41177
Observations	756			
		Non-Defaulted Loans		
Leverage	7.6708	62.8263	-71.5	896
Other leverage	.7337	2.5655	-14.6808	62.5
Coverage	.0941	1.9539	-32.3	12.4118
Observations	708			
		Defaulted loans		
Leverage	3.2345	10.2605	-3.2214	50.5
Other leverage	1.3054	1.2722	0.0326	6.8214
Coverage	.1502	.4266	-1.1222	.9831
Observations	48			

Table 5: Descriptive Statistics CIC Banque SNVB, Model II variables

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
		All loans		
Leverage	.759306	.5718016	.0055494	13.67742
Profitability	.2283852	.9898789	-.702163	26.45161
Liquidity	€ 389,955	1,554,947	-491,000	25,000,000
Length (months)	65.4934	38.13695	6	240
Amount	€ 63,729.5	144,551.7	1,456.19	2,457,000
		Non defaulted loans		
Leverage	.7489	.5790	.0055494	13.6774
Profitability	.2284	1.0171	-.3702	26.4516
Liquidity	€ 408,484.7	1,603,458	-273,000	25,000,000
Length (month)	64.7268	36.7919	6	240
Amount	€ 64,232	147,781.8	1,520	2,457,000
Observations	708			
		Defaulted loans		
Leverage	.91485	.4266	.1399	2.7295
Profitability	.2285	.4204	-.7022	1.8522
Liquidity	€ 68,510.42	217,730.3	-491,000	613,700
Length (month)	76.8333	53.53	24	240
Amount	€ 56,296.51	83,876.07	1,456.19	488,000
Observations	48			

Table 6: Logistic Regression Results of Probability of Default using Model I

Variable	*Coefficient Estimate*	*Standard Error*	*Chi-square*	*P>Chi-Square*
Intercept	-2.72	.15556	-17.49	0.000
Leverage	-0.0259	0.00637	-0.41	0.684
Other leverage	0.0392	0.03179	1.23	0.217
Coverage	0.0174	0.09314	0.19	0.852
Likelihood ratio			1.62	0.6556
Log likelihood	-178.094			
Observations	756			
Defaulted loans	48			
Percent defaulted	6.35 %			

Predictive ability of model I (cutoff 7% default)

Correct	*Sensitivity*	*Specificity*
92.74%	6.25%	98.59%

Table 7: Logistic Regression Results of Probability of Default using Model II

Variable	*Coefficient estimate*	*Standard Error*	*Chi-square*	*P>Chi-Square*
Intercept	-3.09140**	.34247	-9.03	0.012
Leverage	.91582*	.36272	2.52	0.045
Profitability	-.46719*	.23322	-2.00	0.040
Liquidity	-1.86E-06**	9.08E-07	-2.05	0.000
Likelihood ratio			18.17	0.0004
Log likelihood	-169.8172			
Observations	756			
Defaulted loans	48			
Percent defaulted	6.35%			

Predictive ability of the model (cutoff= 7% default)		
Correct	*Sensitivity*	*Specificity*
67.02%	64.58%	67.18%

*, ** represent statistical significance at the 5% and 1% level, respectively.

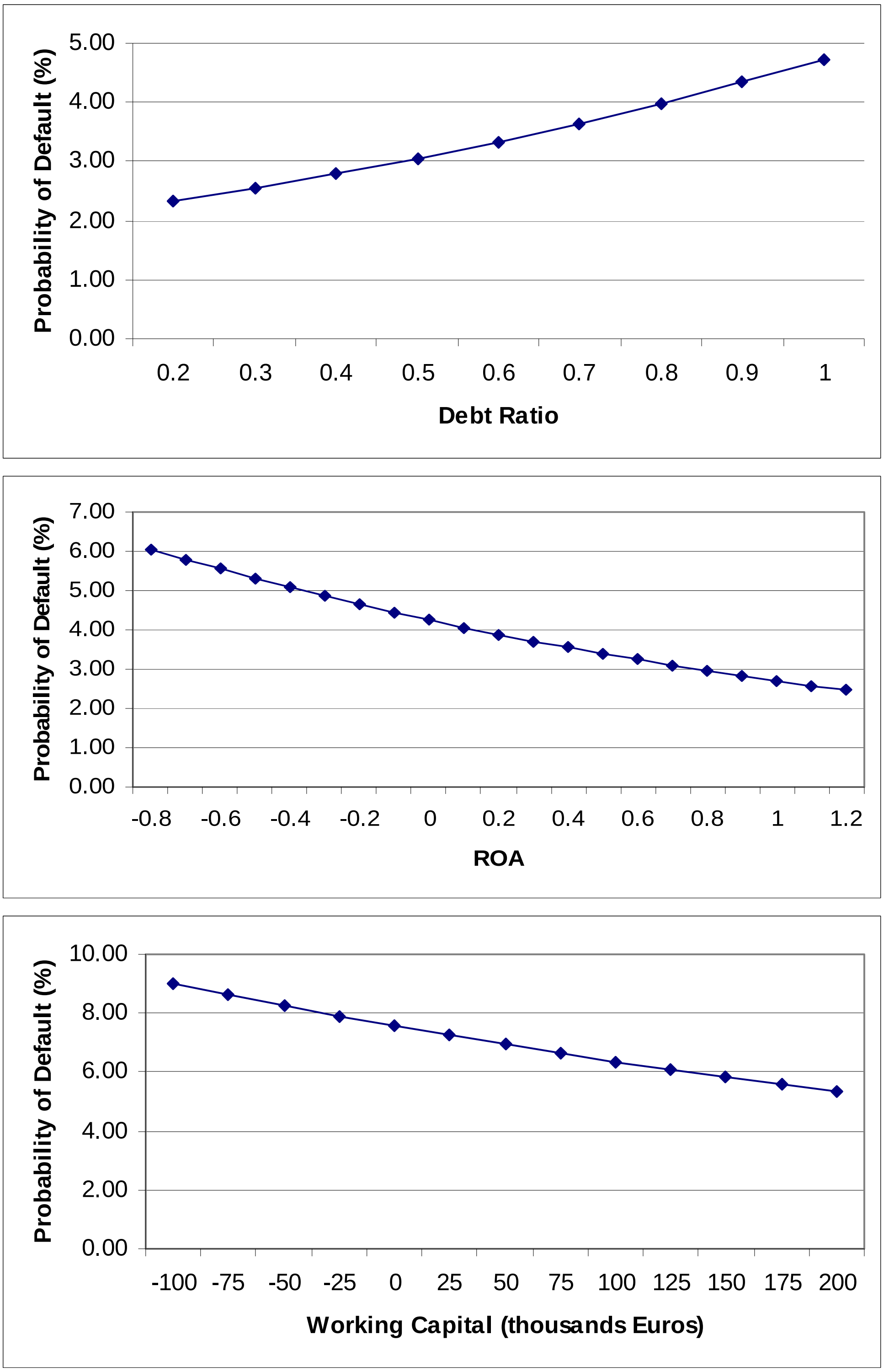

Figure 3: Probability of default as debt ratio, ROA or working capital varies

Table 8: Logistic Regression Results of Probability of Default in the CIC-Banque SNVB Portfolio with Loan Length

Variable	*Coefficient estimate*	*Standard Error*	*Chi-square*	*P>Chi-Square*
Intercept	-3.5961**	.4345	-8.28	0.000
Leverage	.9386**	.3658	2.57	0.010
Profitability	-.4639*	.2323	-2.00	0.046
Liquidity	-1.82E-06*	8.92E-07	-2.04	0.042
Length	0.0068*	.0033	2.07	0.039
Likelihood ratio			22.04	0.0002
Log likelihood	-167.8813			
Observations				
Defaulted	756			
loans	48			
Percent defaulted	6.35%			

Predictive ability of the model (cutoff 7% default)		
Correct	*Sensitivity*	*Specificity*
69.39%	56.25%	70.28%

*, ** represent statistical significance at the 5% and 1% level, respectively.

Table 9: Logistic Regression Results of the Probability of Default in the CIC-Banque SNVB

Portfolio with Commitment Amount

Variable	*Coefficient estimate*	*Standard Error*	*Chi-square*	*P>Chi-Square*
Intercept	-3.1545**	.3485	-9.05	0.000
Leverage	.9009*	.3650	2.47	0.014
Profitability	-.4547*	.2315	-1.96	0.049
Liquidity	-1.98E-06*	8.85E-07	-2.24	0.025
Commitment amount	1.63E-06	1.61E-06	1.01	0.313
Likelihood ratio			19.00	0.0008
Log likelihood	-169.403			
Observations	756			
Defaulted loans	48			
Percent defaulted	6.35%			

Predictive ability of the model (cutoff 7% default)

Correct	*Sensitivity*	*Specificity*
67.94%	58.33%	68.59%

*, ** represent statistical significance at the 5% and 1% level, respectively.

Table 10: Logistic Regression Results of the Probability of Default for Loans associated to Business Specialized in Agriculture, Wine production, Agricultural Services and Others

Variable	*Agricultural*	*Wine production*	*Services*	*Others*
Intercept	-2.4944**	-2.0079*	-2.6898	-3.3958**
Leverage	.4141	-.3466	-.4262	1.6955**
Profitability	-2.3695	-1.9268	-.2829	-.8328**
Liquidity	-8.71E-06**	-1.54E-06	-1.01E-05	-1.25E-07
LR chi-square	20.24*	4.59	4.22	10.23*
Log likelihood	-28.4999	-53.7932	-19.9123	-52.1999
Observations	141	295	166	156
Defaulted loans	11	13	17	7
Percent defaulted	7.8%	4.40%	10.24%	3.2%
Correct	76.60%	52.07%	89.54%	39.64%
Sensitivity	63.64%	21.43%	88.24%	0.00%
Specificity	77.69%	87.23%	38.67%	98.00%

*, ** represent statistical significance at the 5% and 1% level, respectively.