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USING A NEURAL NETWORK-BASED METHODOLOGY FOR CREDIT–RISK EVALUATION OF A TUNISIAN BANK

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Abstract

Credit–risk evaluation is a very important and challenging problem for financial institutions. Many classification methods have been suggested in the literature to tackle this problem. Neural networks have especially received a lot of attention because of their universal approximation property. This study contributes to the credit risk evaluation literature in the MENA region. We use a multilayer neural network model to predict if a particular applicant can be classified as solvent or bankrupt. We use a database of 1100 files of loans granted to commercial and industrial Tunisian companies by a commercial bank in 2002 and 2003. Our main results are: a good capacity prediction of 97.1% in the training set and 71% in the validation set for the non cash-flow network. The introduction of cash-flow variables improves the prediction quality to 97.25% and 90% respectively both in the in-sample and out-of-sample sets. Introduction of collateral in the model substantially improves the prediction capacity to 99.5% in the training dataset and to 95.3% in the validation dataset.

ملخص

يمثل تقييم مخاطر الائتمان مشكلة هامة تنطوى على تحد كبيرٍ للمؤسسات المالية. وقد اقترحت الأدبيات أساليب تصنيف كثيرة للتعامل مع هذه المشكلة. وتحظى الشبكات الإقليمية على وجه الخصوص بقدر كبير من الاهتمام نظراً لما تتميز به من خاصية التقريب الشامل. تساهم هذه الدراسة فى أدبيات تقييم مخاطر الائتمان فى منطقة الشرق الأوسط وشمال أفريقيا. نستخدم نموذج شبكة إقليمية متعددة المستويات للتنبؤ بما إن كان يمكن تصنيف طالب قرض معين على أن لديه سيولة أم أنه مفلس. ونستخدم قاعدة بيانات من 1100 ملف لقروض منحت لشركات تجارية وصناعية تونسية من بنك تجارى فى عامى 2002 و2003. النتائج الأساسية التى توصلنا إليها هى: قدرة تنبؤ جيدة بنسبة 97.1% فى مجموعة التدريب وبنسبة 71% فى مجموعة التأكيد لشبكة التدفق غير النقدى. يحسن إدخال متغيرات التدفق النقدى جودة التنبؤ إلى 97.25% و90% على التوالى فى المجموعتين داخل وخارج العينة. يؤدى إدخال الرهن إلى النموذج إلى تحسن كبير فى إمكانية التنبؤ إلى 99.5% فى مجموعة بيانات التدريب وإلى 95.3% فى مجموعة بيانات التأكيد.

Introduction

Deciding whether or not to grant a loan is a key decision financial institutions have to make every day, especially for short-term commercial loans that are frequently subject to renewal. In effect, bank's credit decision gains in efficiency if it can prevent significant losses by obtaining a solid understanding of who will default on a credit. Determining the symptoms that lead to bad loans can be an effective way of reducing credit risk by pointing out high-risk applicants who should be avoided.

Until recently, in developing countries, this decision used to be based on the traditional approach, which takes into account various quantitative as well as subjective factors, such as liquidity, leverage, earnings, reputation, etc. According to this information and by merely inspecting the application form details, the credit expert used a judgmental approach to decide upon the creditworthiness of the applicant.

But since June 2004, the Basel Committee on Banking Supervision issued a revised framework on International Convergence of Capital Measurement and Capital Standards. Following the "internal ratings-based" (IRB) approach of Basel II, banking institutions will be allowed to use their own internal measures for key drivers of credit risk as primary inputs to their minimum regulatory capital calculation (McDonough ratio).

European countries started to calculate McDonough ratio since 2006. In Tunisia, the Central Bank issued a note in which it called upon banks to introduce (IRB) approach[1], and some banks have already started working on it[2].

In February 2006, the Basel Committee on Banking Supervision issued a consultative document for comment. This document was intended to provide banks and supervisors with guidance on sound credit risk assessment and valuation policies and practices for loans regardless of the accounting framework applied. Principle 3 of this document states that "A bank's policies should appropriately address validation of any internal credit risk assessment models »[3]. In paragraph sixteen, it is stated that "Models may be used in various aspects of the credit risk assessment process including credit scoring, estimating or measuring credit risk at both the individual transaction and overall portfolio levels, portfolio administration, stress testing loans or portfolios and capital allocation".

The implementation of this principle turns out to be a daily decision based on a binary classification problem distinguishing good payers from bad payers. Certainly, assessing the insolvency plays an important role, since a good estimate (related to a borrower) can help decide whether to grant the requested loans or not. The Basel Committee proposes a choice between two broad methodologies for calculating their capital requirements for credit risk, either an external mapping approach or an internal rating system.

Although the external mapping approach is difficult to apply because of the unavailability of external rating grades, the internal rating is easy to implement since numerous methods have been proposed in the literature to develop credit-risk evaluation models[4]. These models include traditional statistical methods (like for example, logistic regression, Steenackers and Goovaerts (1989), nonparametric statistical models (such as k-nearest neighbor, Henley and Hand (1997), classification trees, Davis et al. (1992) and neural network (NNs) models, Desai

[1] Circulaire aux établissements de crédits N° 2006-19 portant sur le contrôle interne.

[2] For Example Amen Bank announced its intension to evaluate credit risk according to the IRB method by 2008.

[3] "Sound Credit Risk Assessment and Valuation for Loans », Consultative Document, Bank for International Settlements Press & Communications, Basel (November 2005).

[4] Especially, the super prime crisis, which shakes down the American and European countries and shows the fragility of banking sector and throw some doubt on the accuracy and usefulness of agency ratings.

et al. (1996). NNs have served as versatile tools for data analysis in a variety of complex environments. In finance, they have been successfully applied to bankruptcy and loan-default prediction and credit evaluation (see West 2000, Wu and Wang 2000, Atiya 2001 and Pang, Wang and Bai 2002). One of their first applications to bankruptcy prediction problems were those of Odom and Sharda (1990). These authors showed that NNs outperformed the Altman's multivariate discriminant analysis (MDA) by more than 10%[5]. Furthermore, compared to other prediction models, NNs present at least three significant advantages. The first is their ability to model complex relationships an analyst might not be aware of. For example, when the banker believes that the likelihood of a loan repayment can be explained by variables, without insufficient foundation theory, the NNs can provide the additional intelligence for successful modeling. The second is, no matter what analytical tool is best in an application, NNs can often be used as a benchmark of what might be possible using another method. The third one is that, as organizations are increasingly pressed to make credit decisions that are both quick and accurate, NNs can assist in speeding up the decision process while maintaining or improving the success rate of credit decisions[6]. That's why we choose to use them in this study.

Our research question is: how banks in the MENA region can develop fairly accurate quantitative prediction models that can serve as very early warning signals for counterparty defaults. Previous work looks at business failure prediction from the mid-term and long-term prospects (failure vs. non failure). In our paper, we look at the short-term prospect (payment vs. nonpayment of the short term credit at maturity). We also consider the case of a bank that wants to use prediction model to assess its credit risk[7].

Specifically, we use a multilayer neural network model to help the credit–risk manager in explaining why a particular applicant is classified as either bad or good. The neural nets parameters will be set using an optimization procedure analogous to the gradient –in the classical topology– and a feed forward neural network with ad hoc connections.

We use a database of 1100 files of loans granted to commercial and industrial Tunisian companies by a commercial bank in 2002 and 2003. We choose to work with short-term commercial loans because they represent the largest part of the loans portfolio and are subject to renewal every year. Since neural network approaches rely on analyzing balance sheets and other financial ratios to assess the default likelihood of firms and classify them in order to determine which businesses will be safe and which will be not repaying, the database includes financial and non-financial data. Common financial ratios and some qualitative variables, such as debt covenant, firm size and industry, will be used.

The remainder of this paper is organized as follow. In section 2 and 3, we provide the theoretical background supporting our research question and our research design respectively. In section 4, we describe data and methodology. In Section 5, we present our results and their interpretations. Finally, Section 6 concludes the paper and presents some limits.

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[5] The NN achieved a Type I correct classification accuracy in the range of 77.8% to 81.5% (depending on the training setup), and a Type II accuracy in the range of 78.6% to 85.7%. The corresponding results for MDA were in the range of 59.3% to 70.4% for Type I accuracy, and in the range of 78.6% to 85.7% for Type II accuracy.

[6] The advent of data storage technology has facilitated financial institutions' ability to store all information regarding the characteristics and repayment behaviour of credit applicants electronically. This has motivated the need to automate the credit granting decision by using statistical or machine learning algorithms.

[7] See failure prediction in Tunisia by Matoussi & al. 1999, financial distress prediction using Neural Networks by Abid & Zouari 2000, financial distress in Egypt by El-Shazly 2002, credit scoring model for Turkey's micro & small enterprises by Davutyan 2006.

Credit Risk Evaluation of Banks: Theory and Empirical Modeling

To this date, credit risk remains a major concern for lenders worldwide. The more they know about the creditworthiness of a potential borrower, the greater their chance to maximize profits, increase market share, minimize risk and reduce the financial provision that must be made for bad debt. We present the theoretical foundation of the credit risk problem and the empirical modeling of its evaluation successively.

The Roots of the Credit Risk Problem: Agency Theory

The problem: One of the most fundamental applications of agency theory to the lender-borrower problem is the derivation of the optimal form of the lending contract. In the debt market, the borrower usually has better information about the project to be financed and its potential returns and risk. The lender, however, doesn't have sufficient and reliable information concerning the project to be financed. This lack of information in quantity and quality creates problems before and after the transaction takes place. The presence of asymmetric information normally leads to moral hazard and adverse selection problems. This situation illustrates a classical principal-agent problem.

The principal-agent models of the agency theory may be divided into three classes according to the nature of information asymmetry. First, there are moral hazard models, where the agent receives some private information after signing the contract. Moral hazard refers to a situation in which the asymmetric information problem is created after the transaction occurs. Since the borrower has relevant information about the project the lender doesn't, the lender runs the risk that the borrower will engage in activities that are undesirable from the lender's point of view because they make it less likely that the loan will be paid back. These models are qualified as models with ex-post asymmetric information.

Second, we find adverse selection models, where the agent already has private information before signing the contract. Adverse selection refers to a situation in which the borrower has relevant information that the lender lacks (or vice versa) about the quality of the project before the transaction occurs. This happens when potential borrowers, who are the most likely to produce an undesirable (adverse) outcome (bad credit risks), are the ones who are most active to get a loan and are thus most likely to be selected. In the simplest case, lenders' price cannot discriminate between good and bad borrowers, because the riskiness of projects is unobservable. These models are known as models with ex-ante asymmetric information. Finally, signaling models, in which the informed agent may reveal his private information through the signal which he sends to the principal.

The solution: This problem is traditionally considered in the framework of costly state verification, introduced by Townsend (1979). The essence of the model is that the agent, who has no endowment, borrows money from the principal to run a one-shot investment project. The agent is faced with a moral hazard problem. Should he announce the true value or should he lower the outcome of the project? This situation describes an ex-post moral hazard. We can also face a situation of ex-ante moral hazard, where the unobservable effort by agent during the project realization may influence the result of the project. Townsend (1979) showed that the optimal contract which solves this problem is the so called standard (or simple) debt contract. This standard debt contract is characterized by its face value, which should be repaid by the agent when the project is finished. As another theoretical justification for simple debt contract was considered by Diamond (1984), where the costly state verification was replaced by a costly punishment. Hellwig (2000, 2001) showed that the two models are equivalent only under the risk neutrality assumption. However, when we consider the introduction of risk aversion, the costly state verification model still works, but the costly punishment model does not survive.

To overcome the asymmetric information problem and its consequences on credit risk assessment in the real world, banks use either collateral or bankruptcy prediction modeling or both. The next subsection will deal with this aspect.

Credit Risk Evaluation: Empirical Modeling

After the high number of profile bank failures in Asia, the research activity on credit risk took a step further. As a result, the regulators recognize the need and urge banks to utilize cutting edge technology to assess the credit risk in their portfolios. Measuring the credit risk accurately also allows banks to engineer future lending transactions, so as to achieve targeted return/risk characteristics. The assessment of credit risk requires the development of fairly accurate quantitative prediction models that can serve as very early warning signals for counterparty defaults[8].

There are two main approaches commonly addressed in the literature. In the first approach, the structural or market based models, the default probability derivation is based on modeling the underlying dynamics of interest rates and firm characteristics. This approach is based on the asset value model originally proposed by Merton (1974), where the default process is endogenous, and relates to the capital structure of the firm. Default occurs when the value of the firm's assets falls below some critical level. In the second approach, the empirical or accounting based models, instead of modeling the relationship of default with the characteristics of a firm, this relationship is learned from the data. Since the work of Beaver (1966) and Altman (1968), bankruptcy prediction has been studied actively by academics and practitioners. Many models have been proposed and tested empirically. Altman's popular Z-Score (Altman, 1968) is an example based on linear discriminant analysis, and was used to predict the probability of default of firms. Ohlson's O-Score (Ohlson, 1980) is based on generalized linear models. Generalized linear models or multiple logistic regression models have been used either to identify the best determinants of bankruptcy or the predictive accuracy rate of their occurrence. Neural network models were adapted and used in bankruptcy prediction. Their high power of prediction makes them a popular alternative with the ability to incorporate a very large number of features in an adaptive nonlinear model (Kay and Titterington, 2000).

Empirical Research Design

The prediction of financial distress is a widely studied topic since it can have significant impact on bank lending decisions and profitability. Several methods and techniques have been suggested in the literature to tackle these decisions. The early empirical approaches were those of Beaver (1966), Altman (1968), and Ohlson (1980). However, these approaches were either very simple (Beaver 1963) or essentially linear models (Altman 1968 and Ohlson 1980). NNs approach started to be used for bankruptcy prediction in 1990 and they are still actively used now [9]. The reason why they received a lot of attention is their universal approximation property and their excellent ability to classify data (especially loan applications)[10]. Neural networks grew out of research in Artificial Intelligence; specifically,

[8] "To get an idea about the potential impact of the bankruptcy prediction problem, we note that the volume of outstanding debt to corporations in the United States is about $5 trillion. An improvement in default prediction accuracy of just a few percentage points can lead to savings of tens of billions of dollars," (Atiya 2001, 929).

[9] The use of artificial neural networks began in the 40s, but their applications in finance are more recent. According to the bibliography research by Wong, Bodnovitch and Selvi (1995), the early experimentations started in 1988 and the first paper on bankruptcy prediction was published in 1990.

[10] "NNs have generally outperformed the other existing methods. Currently, several of the major commercial loan default prediction products are based on NNs. For example, Moody's *Public Firm Risk Model* is based on

attempts to mimic the fault-tolerance and capacity to learn from biological neural systems by modeling the low-level structure of the brain (see Patterson, 1996)[11].

The majority of the NN approaches to default prediction use multilayer networks. 'Feed-forward' NNs are perhaps the most popular network architecture in use today – due originally to Rumelhart and McClelland (1986). They are sometimes also referred to as 'back-propagation NNs' or 'multi-layer perceptrons (Ripley, 1996).

The feed-forward network architecture is composed of an input layer, one or more hidden layers and an output layer. More precisely, feed-forward NNs have units with one-way connections, such that these units can always be arranged in layers so that connections go from one layer to another. This is best seen graphically, see Figure 1.

A network such as Figure 1 represents a function from inputs to outputs (equation 1). Each unit sums its inputs and adds a constant (the 'bias') to form a total input x_j and applies a function f_j to x_j to give output y_j. The links have weights w_{ij} which multiply the signals traveling along them by that factor.

$$f_k(x) = f_0\left(\alpha_k + \sum_{i=1}^{N} u_{ik} x_i + \sum_{j=1}^{M} v_{jk} f_h\left(\beta_j + \sum_{i=1}^{N} w_{ij} x_i\right)\right), \qquad (1)$$

Here N, M and K are the number of input nodes (the number of explanatory variables), the number of nodes in the hidden layer (s) and the number of output nodes (which is the number of possible classes) respectively (Aas et al., 1999).

The general definition allows either more than one hidden layer or 'skip-layer' connections directly from input to output. It is also possible to avoid skip-layer connections, in which case equation (1) reduces to:

$$f_k(x) = f_0\left(\alpha_k + \sum_{j=1}^{M} v_{jk} f_h\left(\beta_j + \sum_{i=1}^{N} w_{ij} x_i\right)\right), \qquad (2)$$

Where f_h and f_o are denoted activation functions.

The function $f_h(x)$ of the hidden layer is always taken to be the logistic function (Aas et al., 1999): $f_h(x) = \frac{exp(x)}{1 + exp(x)}$, while the output function $f_o(x)$ may either be logistic or linear: $f_0(x) = \frac{exp(x)}{1 + exp(x)}$ or $f_0(x) = x$.

A neural network with no hidden layers is identical to the generalized linear model. However, a NN with one hidden layer using nonlinear activation functions, such as the logistic, is nonlinear in the parameters and corresponds to multivariate nonlinear logistic regression (Aas et al., 1999).

NNs as the main technology. Many banks have also developed and are using proprietary NN default prediction models,"(Atiya 2001, 930).

[11] Neural networks are applicable in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists, even when that relationship is very complex and not easy to articulate in the usual terms of "correlations" or "differences between groups.".

In practice the main issues are how the parameters and weights should be estimated, and how the architecture is selected. The parameters can be estimated in at least three ways.

If least squares fitting are used, we minimize (equation 3):

$$E = \sum_{p=1}^{P} \sum_{k=1}^{K} \left(y_k^p - f_k\left(x^p\right)\right)^2 . \qquad (3)$$

If the entropy (the maximum conditional likelihood) fitting is used, we minimize (equation 4):

$$E = \sum_{p=1}^{P} \sum_{k=1}^{K} \left[y_k^p \, log \frac{y_k^p}{f_k\left(x^p\right)} + \left(1 - y_k^p\right) log \frac{1 - y_k^p}{1 - f_k\left(x^p\right)} \right] \qquad (4)$$

Finally, if we use the softmax method, the output function must be linear and we minimize:

$$E = \sum_{p=1}^{P} \sum_{k=1}^{K} y_k^p \, log \frac{y_k^p}{p_k^p} \text{ ; where: } p_k^p = \frac{exp\left(f_k\left(x^p\right)\right)}{\sum_{j=1}^{K} exp\left(f_k\left(\left(x^p\right)\right)\right)} .$$

For all three methods weight decay may be used. This means that instead of E we minimize (equation 5):

$$E + \lambda\left(\sum_{k=1}^{K} \alpha^2 + \sum_{k=1}^{K} \sum_{i=1}^{N} u_{ik}^2 + \sum_{k=1}^{K} \sum_{i=1}^{M} v_{jk}^2 + \sum_{j=1}^{M} \beta_j^2 + \sum_{k=1}^{N} \sum_{i=1}^{M} w_{ij}^2 \right). \qquad (5)$$

The use of weight decay seems both to help the optimization process and to avoid over-fitting. Suggestions have been made that $\lambda \in (0.01, 0.1)$ for the entropy fit (Aas et al., 1999)[12].

Sample and Data

When lenders want to know about a company's ability to pay debts on time, they assess its credit risk. To understand credit risk levels of users, financial institutions normally collect large amount of information on borrowers. The basic part of this information relies on the lessons of the traditional financial analysis. Financial analysis of a potential borrower begins with an understanding of the firm, its business, its key risks and success factors. Then, commonly financial ratios and some qualitative variables are calculated from available data. Statistical methods based on data mining techniques are used to analyze or to determine risk levels involved in credits and loans, namely the default risk levels.

We start by presenting our sample and the nature and sources of our primary data. Then, we explain how our variables are justified and measured.

Sample Selection and Variables Measurement

Let's recall that our objective is to use neural network methodology for default prediction of a bank's commercial loans. But, in order to solve a problem using neural networks, we need to gather data for training purposes. The training data set includes a number of cases, each

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[12] A comprehensive discussion of neural networks can be found in Ripley (1996).

containing values for a range of input and output variables. The first decision we need to make is which variables to use. The second one concerns the subjects whose behavior we want to predict. For our case the variables are indicators of default risk and the subjects are borrowers. The data collected for our investigation came from a large private commercial bank (BIAT). We chose a private bank in order to avoid the potential inefficiency of public banking sector, whose decision is sometimes dictated by government choices. We also chose to work with short-term commercial loans because they represent the largest part of loans and are subject to renewal every year[13].

We use a database of 1100 files granted to 550 commercial and industrial Tunisian companies by a commercial bank in 2002 and 2003. This period was chosen because it related to a Central Bank instruction asking banks to provide credit risk classes for their borrowers. In BIAT's case, it classifies these files into five clusters, each one corresponding to a risk class by the end of every trimester. Files without delay of payment signal the healthy firms. The four remaining classes correspond to four riskier classes of three, six, nine and one year (or more) delay of payment respectively. We group these four classes in one class (risqué companies). Panels 1 and 2 of Table 1 classify our sample by risk class and industry.

Variables Measurement

Dependent Variable

Our dependant variable is the probability of default. We use a dummy variable, which equals 0 if the classified as healthy and 1 otherwise. Hence:

Y = 0 if no delay of payment

Y = 1 if there is more than 3 month delay

Independent Variables

Default risk prediction relies in general on a good appraisal of the couple risk-return of a company. Financial ratios drawn from financial statements (balance sheet, income and cash flow statement) are usually used. Financial ratio analysis groups the ratios into categories which tell us about different facets of a company's finances and operations (liquidity, activity or operational, leverage and profitability).

In our experiment we retain 27 financial and non financial indicators, 24 of them are financial ratios and 3 are not. The financial indicators are inspired by Altman's popular Z-Score and recommended textbooks in financial statement analysis and valuation (Berstein and Wild 1998; Revsine, Collins and Johnson 1999; and Palepu, Healy and Bernard 2000). The object of this subsection is to discuss why such particular indicators have been chosen and how they were measured.

Liquidity Ratios

These ratios give a picture of a company's short term financial situation or solvency. Liquidity refers to the ability of company resources to meet short term cash requirements. A lack of liquidity may indicate the inability of a company to take advantage of favorable discounts or profitable opportunities. A company's short term liquidity risk is affected by the timing of cash inflows and outflows along with its prospects for future performance. Short term is conventionally viewed as a period up to one year, though it is identified with the

[13] Loans with maturities of one year or less comprise more than half of all commercial bank loans (Revsine and al. 1999). For the case of BIAT this ratio was around 40% during 2006 and 2007.

normal operating cycle of a company (the time period encompassing the buying-producing-selling-collecting cycle).

A company's customers and suppliers of products and services are affected by short term liquidity problems. Implications include a company's inability to execute contracts and to damage important customer and supplier relationships[14]. When a company's owners possess unlimited liability (proprietorship and certain partnership), a lack of liquidity endangers their personal assets. To creditor of a company, a lack of liquidity can yield delays in collecting interest and principal payments or the loss of amounts due to them. In brief, when a company fails to meet its current obligations, its continued existence is doubtful.

Working capital is widely used to measure short term liquidity. Working capital is defined as the excess of current assets over current liabilities. When current liabilities exceed current assets, the firm has a working capital deficiency. **WC** is important as a measure of liquid assets because it provides a safety cushion to creditors. It is also a liquid reserve a company may use to face contingencies and uncertainties surrounding balance of cash inflows and outflows. When it is significantly negative, the company might default on some payments.

Operating activity is also an important measure of liquidity. This can be seen by decomposing WC in account receivable and inventory. For most companies selling on credit, account and notes receivable are an important part of WC. In assessing liquidity, it is necessary to measure the quality and liquidity of receivables. Liquidity refers to the speed in converting account receivables to cash. Another component to watch is the relation between the provision for doubtful accounts and gross accounts receivable. Increases in such component suggest a decline in the collection of receivables and vice versa.

Furthermore, an increase in inventory means a drop in sales. Such situation may create a liquidity problem since loan repayment usually comes from the routine conversion of these current assets into cash.

Cash flows: The static nature of the current ratio and its inability to recognize the importance of cash flows in meeting maturing obligations has led to a search for a dynamic measure of liquidity. Since liabilities are paid with cash, a ratio comparing operating cash flow to current liabilities overcomes the static nature of the current ratio, which could give a better insight of liquidity risk.

The ratios R1 to R5 (Table 2) capture the liquidity risk of a firm according to the approaches developed above. While R2 to R5 should have a positive impact on healthiness, R1 (provision for doubtful accounts) will negatively impact the health of a company.

Leverage Ratios and Long Term Solvency

Beyond advantages of excess return to financial leverage and the tax deductibility of interest, a long term debt position can yield other benefits for equity holders (avoidance of earnings dilution for growth companies). However, the fundamental risk with leverage is the risk of inadequate cash under conditions of adversity. While certain fixed charges can be postponed

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[14] "The reasons for the current ratio's widespread use as a measure of liquidity include its ability to measure:

Current liability coverage: the higher the amount of current assets to current liabilities, the greater assurance we have in current liabilities being paid.

Buffer against losses: the larger the buffer, the lower the risk. The current ratio shows the margin of safety available to cover shrinkage in noncash current asset values when ultimately disposing or liquidating them.

Reserve of liquid funds: the current ratio is relevant as a measure of the margin of safety against uncertainties and random shocks to a company's cash flows. Uncertainties and shocks, such as strikes and extraordinary losses, can temporarily and unexpectedly impair cash flows." (Bernstein and Wild 1998, 412).

in times of cash shortages, the fixed charges related to debt (interest and principal repayments) cannot be postponed without adverse effect. An excess of leverage runs a risk from loss of financing flexibility, which compromises the company's ability to raise funds, especially in periods of adverse market conditions.

Capital structure measures serve as screening devices. The relation between liabilities and equity capital is an important factor in assessing long term solvency. The higher the proportion of debt, the larger the fixed charges of interest and principal, and the greater the likelihood of insolvency during periods of earnings decline or hardship.

There are several variations in debt ratios. R6 to R11 (Table 2) are those retained in our analysis. While R6 (debt coverage by cash flow) should have a negative impact on the probability of failure, this probability of failure should be positively associated with ratios R7 to R11.

Nevertheless, even if debt ratios are useful for understanding the financial structure of a company, they provide no information about its ability to generate a stream of inflows sufficient to make principal and interest payments. That assessment of insolvency is completed by other indicators involving flows (like operating income, operating cash-flow, interest and principal repayment). Without a doubt, creditors are primarily concerned with assessing a firm's ability to meet its debt obligations through timely payment of principal and interest. Commercial banks and other financial institutions form opinions about a company's credit risk by comparing current and future debt-service requirements to estimate the company's current and expected future cash flows.

There are a number of ratios which help the analyst in this area (R12 to R14 in Table 2). The probability of failure should be negatively associated with these ratios.

Profitability Ratios

A company performance can be analyzed in several ways. Revenue, gross profit and net income are the performance measures commonly used. However, none of these measures alone can act as a comprehensive proxy for performance because of the interdependency of business activities.

Profitability ratios use margin analysis and show the return on sales and capital employed. Profit margins reflect the firm's ability to produce a product or a service at a low cost or a high price. Nevertheless, profit margins are not direct measures of profitability because they are based on total operating revenue, not on the investment made in assets by the firm or the equity investors. To complete the profitability analysis, it is recommended to use indicators based on the firm's earnings. Another related indicator, widely used, and less prone to management manipulation is the cash flow.

Among profitability indicators, return on invested capital (ROI) is probably the most widely recognized measure of firm performance. It is a good indicator of a company's long-term financial strength. It uses key summary measures from both income statement and balance sheet to assess profitability. Other measures of performance are not of lower interest. They enable us to better estimate both the return and risk of a company. They allow us to distinguish between performance attributed to management (operating decision) and those less tied to management (taxes and selling prices).

Ratios R15 to R19 (Table 2) have been used in our study to gauge the perspective of borrowers. There should be a negative link between these variables and the probability of default.

In order to improve the quality and performance of our prediction model, we retain in our analysis other ratios used by the bank to assess its credit decision (R20 to R24 in Table 2). The ratios R20 (net fixed assets over total debt), R23 (total asset turnover) and R24 (fixed asset turnover) will be negatively associated to the probability of default. However, Ratios R21 (short term debt to sales) and R22 (financial expenses to revenue) should be positively associated to failure probability.

Non Financial Variables

Besides, common financial ratios, some other variables are either suggested by the theory (collateral) or by the banking credit context. We choose three for our investigation: collateral, firm size and industry.

Collateral: Collateral plays an important role in bank behavior. In effect, debt holders impose covenants on the firm, restricting the firm's operating, investment and financing decisions. Many models were designed to show the impact of collateral on the borrower-lender relation. Bester (1985), and Besanko and Thakor (1987) build on the ex ante screening model of Stiglitz and Weiss (1981) to infer the signaling role of collateral to solve the adverse selection problem inherent in debt financing under asymmetric information. In a model with two types of projects (high and low risk) and two agents, it was evident that each agent chooses the contract that is best suited to his needs. Low-risk borrowers choose contracts with collateral. High-risk borrowers, in contrast, prefer loans with no collateral. Thus, the equilibrium solution is given by two separating contracts, and as long as these optimal contracts for different types of agents are different, we are in the case of a separating equilibrium[15].

A second class of models focuses on the ex-post monitoring function of banks. Bester (1994) develops a model of debt renegotiation that predicts a positive correlation between expected default risk and collateralization. In this model, a creditor cannot distinguish between strategic default (borrower is cheating), and default due to bad state of nature. The provision of outside collateral will reduce, in that case, the debtor's incentive for strategic default. Rajan and Winton (1995) model the situation where the collateralization decision of an inside bank is observed by less informed agents (thereby transforming private information on borrower quality into public information). Thus, the inside bank is compensated for this externality by a more senior debt position. Since in equilibrium the informed lender tends to collateralize loans with high risk borrowers, there should be a positive association between risk and collateral.

In bankruptcy prediction, this positive correlation between project risk and collateral corresponds to conventional wisdom in banking, which views collateral as a means to lower the risk exposure of a bank (see for example Berger and Udell 1990). We should observe a positive relation between collateral and default risk. In our study this indicator is measured by a dummy variable (1 if collateral and 0 if not).

Firm Size: A company's total assets give some indication on the size of the firm and can be used to get an idea about the solidity of a company. Therefore, it is frequently used as a normalizing factor. However, in the case of our bank (BIAT), the size is not approximated by total assets but by the size of outstanding loans of the borrower. If the total loan (short term and long term) due to the bank is more than one million Dinars, the firm is classified as less risky. But if total loans are under one million Dinars, the firm is classified risky. We will use this indicator in our analysis.

[15] However, if all types of agents prefer to receive the same contract, we are in case of the pooling equilibrium. See Capra, Fernandez, and Raminez (2001)

Industry: The variable industry plays an important role in many areas of empirical research. However in credit risk, this variable doesn't seem to have an impact on the credit decision. Nevertheless, its inclusion in our analysis can be justified by the nature of firms in our sample. Since our sample is composed of commercial and industrial firms, we can say that industrial firms who have more important tangible assets may present a better guarantee for the bank.

Empirical Results

To get a better idea about our data before running the NN model, we will perform a descriptive analysis. We complete this analysis by a test of mean differences between the two risks classes defined above (Table 1).

Descriptive Statistics

The summary statistics and the mean differences can be seen as an analysis similar to Beaver's (1963). Table 3 presents the descriptive statistics of our data.

When we look closely at summary statistics, we find some abnormal results (like a negative mean for R13, R15 and R16). We then check the extreme values (min and max) and find an outlier problem in our data base[16]. Panel 2 of Table 3 shows the summary statistics after eliminating outliers. Then, we run mean differences analysis between the two risk classes (healthy and risky groups). This analysis can give us a proper taste of our data, since such analysis allows us to verify if there is a difference between the two classes in terms of financial ratios. Table 5 recalculates some summary statistics for the two risk classes.

Tables 6 displays the results of the t mean differences test for all financial ratios[17].

Table 6 shows significant mean differences between the two groups for some ratios (R8 to R12, R16, R17 and R21 to R24) and no significant differences for others (R1 to R7, R13 to R15 and R18 to R20). Globally, they tell us that the liquidity risk does not differentiate the two groups. The solvency ratios do better in differentiating the two groups. The ratios retained by the bank are the best in terms of differentiating the two groups. For others indicators (coverage and profitability), the results are mitigated. For example, while the interest coverage ratio (R12) shows a significant difference, the revised interest coverage ratio (R13) does not. Also, while gross profit margin (R16) and return on investment (R17) are significant, gross return on invested capital (R18) and return on equity (R19) are not.

When we look at the relevance of mean differences, we realize that the globally good indicators are abundant in the healthy group, while the bad indicators are higher in the risky group. For example the mean of liquidity ratios (R2 to R6), coverage and profitability ratios (R6, R12 to R17, R23 and R24) are bigger in the healthy group. Provisions for doubtful accounts (R1), and solvency ratios (R7 to R10, R21 and R22) have a higher mean in the risky group.

Let's see now if NNs do a better job in predicting default risk.

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[16] Since our data base was electronic and anonymous, we tried to solve the problem by eliminating outliers. The number observations dropped was around 70. Our final clean sample is composed of 1028 credit files. The clean sample was only used for this part. In NNs model we use the whole sample, since the method resolves the outlier problem automatically.

[17] Before running the t test we verify the normality distribution for all the variables and for each sub-ample. Table 4 show the results.

Neural Networks Results

NNs have been widely used in finance due partly to their excellent ability to classify data. A prime example of a finance application is classifying loans. Analyzing who will default on a loan is a big business for financial institutions. In effect, if the bank succeeds to classify potential borrowers as either healthy or doubtful, it can have a good appraisal and assessment of its credit risk. In this section, we show how NN methodology can do this job. Moreover, we identify which indicators (financial and non financial) perform better in the case of a Tunisian bank.

In our experiment we split our sample of the bank credit files into two sub samples. The first sub-sample is composed of 800 files of short term loan granted to Tunisian companies in 2002 and 2003. The data of this sub-sample is used as a training set (the in-sample set) to construct the prediction NNs models. The second one is composed of 300 files and is used for validation (the out-of sample set). Our experiment relied on the supervised learning paradigm[18].

A typical feed forward network has neurons arranged in a distinct layered topology. The input layer serves to introduce the values of the input variables. The hidden and output layer neurons are each connected to all of the units in the preceding layer.

We build up three types of NNs. The first NN uses data on financial ratios (cash-flows excluded). It will be referred to as 'Non cash-flow NN model'. The second NN uses data on all ratio indicators (cash-flows included). It will be referred to as 'Cash-flow NN model'. The third NN uses all financial and non financial indicators. It will be referred as 'Full information NN model'. For each type of these NNs, we run many experiments with no hidden layer and with one, two, three or four hidden layers. The following notation will be used:

Net 0 (N_i N_o): Network without hidden layer

Net 1 (N_i N_h N_o): Network with one hidden layer

Net 2 (N_i N_{h1} N_{h2} N_o): Network with two hidden layers

Net k (N_i N_{h1} N_{h2} …. N_{hk} N_o): Network with k hidden layers

Where N_i, N_h, N_o represent the number of input layers, the number of neurons in hidden layers and the number of output layers respectively.

In our analysis we use supervised learning algorithms (of which the best known example is back propagation, devised by Rumelhart et. al., 1986). This algorithm uses the data to adjust the net's weights and thresholds so as to minimize the error in its predictions on the training set. If the net is properly trained, it has then learned to model the (unknown) function that relates the input variables to the output variables, and can subsequently be used to make predictions where the output is not known.

Results of the In-sample Set

Panels 1, 2 and 3 of Table 7 show the results for Type 1 and 2 NN models (without and with cash flow ratios). Figures 2, 3 and 4 display the curves of the Mean Square Error (training) for the three types of NN models retained. These figures show the power curves of the three best networks.

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[18] In supervised learning, the network user assembles a set of *training data*. The training data contains examples of inputs together with the corresponding outputs, and the network learns to infer the relationship between the two. Training data is usually taken from historical records.

We can see from these results (Panel 1) that the introduction of hidden layers improves the performance of the model. The MSE drops from 15.5% (Net 00) to 1.9% for the best three hidden layers NN (Net_03 [21 12 12 12 2]). The classification rate is improved from 79.6% to 98.1%. The introduction of cash-flow variables (Panel 2) improves the performance since the Type 2 model gives a better MSE (10.7 % for the no hidden layer and 0.6% for the three hidden layers)[19]. The classification rate is improved from 85.62% to 98.25%[20]. Panel 3 of Table 7 shows that Type 3 model outperforms the two previous models since the MSE is lower and the classification is higher for all versions (without and with hidden layers). The collateral variable has the best contribution. The best version (Net 02 [27 10 8 2]) has the lowest mean square error (0.72%) and the highest classification rate (99.5%).

However before conceding to the superiority of NNs to classify and predict default risk, we need to validate our findings on the out-of-sample set.

Out-of- Sample Validation

Let's recall that the out-of-sample validation will be done on the second sub-sample, which contains data on 300 files of short term loans granted to Tunisian companies in 2003.

Table 7 presents the results of the validation test for the three types of NN models obtained from the training set. We can see form Panel 1 of Table 7 that the best model in training also gives the best performance (with a MSE of 0.3%) in the out-of-sample. The corresponding classification rate is 71%. The introduction of cash-flow indicators (Panel 2) improves the performance of the model in term of classification rate (with a 90% of good classification rate). The classification rate jumped to 95.3% (Panel 3) when we introduced the whole set of indicators. It is worth noting here that the best network (Net_02 [27 10 8 2]) in the training sample is also the best one in the validation with the lowest MSE.

Conclusion

Credit risk problem is a real puzzle in many regards. It is a puzzle for economic agents (lenders and borrowers) because it's the key determinant of the risk premium charged by the lender and supported by the borrower. It is, also, a puzzle for theorists and researchers because it comes from asymmetric information, which causes moral hazard and adverse selection problems. It is, finally, a puzzle for regulators because it is the cause of financial crises coming from incompetence or a wrong approach in handling the credit risk problem. In this paper, we adopt the last perspective.

In its newsletter released on 7 May 2007, the Basel Committee on Banking Supervision reviewed progress and recent initiatives to achieve its strategic objectives of implementation of Basel II. It is stated that areas of potential emphasis include: new measurement approaches for credit risk, the treatment of diversification effects, the assessment of complex counterparty credit risks, the treatment of interest rate risk, and firms' approaches to validation of internal capital assessments. In fact, Basel II was introduced to reflect improved risk measurement and management techniques. It streamlines the minimum capital held against credit risk, and assigns capital against credit and operational risk for the first time, mitigating even further the credit and operational banking risks.

[19] We note that until now Tunisian bankers do not use cash-flow measures in their analysis.

[20] This network is dominated by the four hidden layers network (Net_04 [24 12 12 12 8 2]) in term of MSE. In spite of performance improvement of this network, the global classification rate has decreased. This can be explained by the over-fitting problem. This problem usually occurs when we have a good performance in the training step in terms of MSE, but the model doesn't have a good discrimination power.

In this article we tried to assess the credit risk for a Tunisian bank through modeling the default risk of its commercial loans. We used a data base of 1100 credit files during 2002 and 2003. In order to apply a NN methodology we split our sample into two sub-samples. The first corresponds to the training data (in-sample set) and contains 800 credit files (550 from 2002 and 250 from 2003). The second sub-sample contains 300 credit files (from 2003) and contains the validation data (out-sample set).

Inputs variables were classified in three categories: non cash-flow ratios, cash-flow ratios and non financial variables.

The main results can be summarized as follow:

Non cash-flow variables have a good prediction capacity of 97.1% in the training set and 71% in the validation set.

The introduction of cash-flow variables improves the prediction quality, and the classification rates passed to 97.25% and 90% respectively in the in-sample and out-of-sample sets.

Collateral played an important role in default risk prediction. Its introduction in the model substantially improves the prediction capacity to 99.5% in the training data set and to 95.3% in the validation data set.

If we compare our results with previous studies, we got a better classification than Atiya (2001)[21]. Our model (the full information one) outperforms his model by 14% in the financial ratios model and by 10% in the financial and equity model. By the way, using the same data, we obtained a classification rate of only 75% from a discriminant analysis. Hence, our study confirms the superiority of NN models to other techniques in the prediction of default and the assessment of credit risk evaluation.

These findings are encouraging and in favor of a quick adoption of IRB in Tunisia and MENA region. Our study can be helpful both for banks or regulators. It may help banks to identify the best financial predictor for default risk. It may also help authorities to implement an internal based risk method for assessment of credit risk evaluation.

Our study is however incomplete in the sense that it didn't show how one can use these results in the future implementation of the Basel II accord in Tunisia. This study can be completed by a simulation calculating the percentage of credit failure we could have avoided by using NN modeling for the BIAT and the whole banking system.

Finally, even if the Tunisian banking system may suffer from the absence of reliable data, our findings should give them incentive to build up strong and reliable databases, which will help them to meet the strict requirements of the new Basel Accord.

[21] For the financial ratio system he obtained a prediction accuracy of 84.52% for the in-sample set, and 81.46% for the out-of-sample set. For the financial ratio and equity-based system he obtained a prediction accuracy of 89.41% for the in-sample set, and 85.50% for the out-of-sample set.

References

Aas, K., Huseby, R. B. and Thune, M. (1999), 'Data Mining: A survey,' Report, Norwegian Computing Center. ISBN 82-539-0426-6.

Abid, F. and A. Zouari (2000), "Financial Distress Prediction Using Neural Networks," http://ssrn.com/abstract=355980 or DOI: 10.2139/ssrn.355980.

Altman, E. I. (1968), 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy,' *Journal of Finance* 23, 589–609.

Atiya, A.F. (2001), 'Bankruptcy Prediction for Credit Risk Using Neural Nets: A survey and New Results,' *IEEE Transactions on Neural Nets*, Vol. 12 n.4, 929-935.

Beaver, W. (1966), 'Financial Ratios as Predictors of Failure. Empirical Research in Accounting: Selected Studies,' *Journal of Accounting Research* 5, 71–111.

Berg, D. (2005), 'Bankruptcy Prediction by Generalized Additive Models,' Statistical Research Report No. 1, University of Oslo.

Berger A. N. and G. F. Udell (1990), 'Collateral, Loan Quality, and Bank Risk,' *Journal of Monetary Economics*, 25(1): 21–42, January 1990.

Berstein, L. A. and J.J. Wild (1998), 'Financial Statement Analysis: Theory, Application, and Interpretation,' Sixth Edition, McGraw-Hill.

Besanko, D. and A V. Thakor (1987), 'Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets,' *International Economic Review*, 28(3):671–689.

Bishop, C.M. (1995), 'Neural Nets for Pattern Recognition,' Oxford: Oxford University Press.

Capra, M. C., M. O. Fernandez and I. Raminez (2001), 'The Separating Role of Collateral Requirements in Credit Markets with Asymmetric Information,' Working Paper 23, LINEEX, University of Valencia, May 2001.

Davutyan, N. and S. Özar (2006), 'A Credit Scoring Model for Turkey's Micro & Small Enterprises (MSE's),' 13th Annual ERF Conference, Kuwait, 16 – 18 December 2006.

Diamond, D. W. (1984) 'Financial Intermediation and Delegated Monitoring,' *Review of Economic Studies*, 51(3):393–414, July 1984.

El-Shazly, A. (2002), 'Financial Distress and Early Warning Signals: A Non-Parametric Approach with Application to Egypt,' 9th Annual ERF Conference, Emirates, October 2002.

Gadanecz, B. (2007), 'Recent Initiatives by the Basel-based Committees and Groups,' *BIS Quarterly Review*, September 2007.

Hellwig M. (2000), 'Financial Intermediation with Risk Aversion,' *Review of Economic Studies*, 67(4):719–742.

Hellwig M. (2001), ‘Risk Aversion and Incentive Compatibility with Ex-post Information Asymmetry,’ *Economic Theory*, 18(2):415–438.

Kay, J. and Titterington, M., eds (2000), *Statistics and Neural Nets*, Advances at the Interface, Oxford University Press.

Longstaff, F and E. Schwartz (1995), ‘A Simple Approach to Valuing Risky Fixed and Floating Rate Debt,” *Journal of Finance*, vol. 50, 789–819.

Matoussi H., R. Mouelhi & S. Salah (1999), ‘La Prédiction de Faillite des Entreprises Tunisiennes par la Régression Logistique,’ *Revue Tunisienne des Sciences de Gestion*, (1): 90-106.

Merton, R. (1974), ‘On the Pricing of Corporate Debt: The risk Structure of Interest Rates,’ *Journal of Finance*, Vol. 29, pp. 449–470.

Odom M. and R. Sharda (1990), ‘A Neural Net Model for Bankruptcy Prediction,’ in *Proc. Int. Joint Conf. Neural Nets*, San Diego, CA.

Ohlson, J. A. (1980), ‘Financial Ratios and the Probabilistic Prediction of Bankruptcy,’ *Journal of Accounting Research* 18, 109–131.

Palepu K. G., P. M. Healy et V. L. Bernard (2000), ‘Business Analysis & Valuation Using Financial Statements,’ Second Edition South – Western College Publishing.

Pang, S.L., Y.M. Wang and Y.H. Bai (2002), “Credit Scoring Model Based on Neural Network,” Proc. of the First International Conference on Machine Learning and Cybernetics, Beijing, 4-5 November 2002.

Rajan, R., and A. Winton (1995), ‘Covenants and Collateral as Incentives to Monitor,’ *The Journal of Finance*, Vol. 50, No. 4 (Sep., 1995), 1113-1146

Revsine, L., D.W. Collins and W.B. Johnson (1999), ‘Financial Statement and Analysis,’ Prentice Hall, New Jersey.

Ripley, B. D. (1996), ‘Pattern Recognition and Neural Nets,’ Cambridge University Press, New York.

Stiglitz, J.E. and A. Weiss (1981), ‘Credit Rationing in Markets with Imperfect Information,’ *The American Economic Review*, Vol. 71, No. 3, 393-410

Townsend, R. M. (1979), ‘Optimal Contracts and Competitive Markets with Costly State Verification,’ *Journal of Economic Theory*, 21(2):265–293.

Udo Schmidt-Mohr (1997), ‘Rationing Versus Collateralization in Competitive and Monopolistic Credit Markets with Asymmetric Information,’ *European Economic Review*, 41, 1321–1342, 1997.

Wong, Bodnovitch and Selvi (1995), ‘A Bibliography of Neural Networks Business Applications Research,’ *Expert Systems*, Vol. 12 N°3, 253-262.

West, D, (2000), 'Neural Network Credit Scoring,' *Computer & Operations Research*, 27 (11): 1131-1152.

Wu, C. and X.M. Wang, (2000), 'A Neural Network Approach for Analyzing Small Business Lending Decisions,' *Review of Quantitative Finance and Accounting*, 15 (3): 259-276.

Table 1: Sample Subsets Characteristics

Panel 1: Classification by Default Risk

	2002		**2003**	
	Number of firms	**Percentage**	**Number of firms**	**Percentage**
Healthy companies	433	78.72%	442	80.36%
Risky companies	117	21.28%	108	19.64%
Total sample	**550**	**100%**	**550**	**100%**

Panel 2: Classification by Industry

	Number of firms	**Percentage**
Commercial companies	535	92.3%
Industrial companies	15	2.7%
Total sample	**550**	**100%**

Table 2: Variables Definition and Measure

Risk facet	Code	Variable definition	Variable measure
Liquidity indicators	R1	Account receivable liquidity	$\frac{\text{Provision for doubtful accounts}}{\text{Gross account receivables}}$
	R2	Current ratio	$\frac{\text{Current assets}}{\text{Current liabilities}}$
	R3	Quick ratio	$\frac{\text{Current assets - inventories}}{\text{Current liabilities}}$
	R4	Cash flow ratio	$\frac{\text{Operating cash flow}}{\text{Current liabilities}}$
	R5	Inventory turnover	$\frac{\text{Sales}}{\text{Inventories}}$
	R6	Debt Cash Flow Coverage Ratio	$\frac{\text{Cash flow}}{\text{Total debts}} = \frac{\text{Net Income} + \text{depreciation}}{\text{Total debts}}$
Leverage and solvency indicators	R7	Liabilities to equity ratio	$\frac{\text{Total liabilities}}{\text{Shareholders' equity}}$
	R8	Net debt to equity ratio	$\frac{\text{Short term debt} + \text{long term debt} - \text{cash and marketable securities}}{\text{Shareholders' equity}}$
	R9	Debt to capital ratio	$\frac{\text{Short term debt} + \text{long term debt}}{\text{Short term debt} + \text{long term debt} + \text{shareholders equity}}$
	R10	Long term debt to assets	$\frac{\text{Long term debt}}{\text{Total assets}}$
	R11	Long term debt to tangible assets	$\frac{\text{Long term debt}}{\text{Total tangible assets}}$
	R12	Interest coverage ratio	$\frac{\text{Operating income before taxes and interest}}{\text{Interest expense}}$
	R13	Revised interest coverage ratio	$\frac{\text{operating income before taxes and interest}}{\text{interest expense} + \text{principal}}$
	R14	Cash flow coverage ratio	$\frac{\text{Operating cash flows}}{\text{Interest expense}}$
Profitability indicators	R15	Net profit margin	$\frac{\text{Net income}}{\text{Total operating revenue}}$
	R16	Gross profit margin	$\frac{\text{Earnings before interest and taxes}}{\text{Total operating revenue}}$
	R17	Return on invested capital	$\frac{\text{Net income}}{\text{Total assets}}$
	R18	Gross return on invested capital	$\frac{\text{Earnings before interest and taxes}}{\text{Total assets}}$
	R19	Return On Equity (ROE)	$\frac{\text{Net income}}{\text{Stockholders equity}}$
Ratios used by the bank	R20	Fixed asset to debt ratio	$\frac{\text{Net fixed assets}}{\text{Total debt}}$
	R21	Short term debt to sales ratio	$\frac{\text{Short term debt}}{\text{Total sales}}$
	R22	Financial expenses to revenue ratio	$\frac{\text{Financial expenses}}{\text{Total revenues}}$

	R23	Total asset turnover	$\frac{\text{Sales}}{\text{Total assets}}$
	R24	Fixed asset turnover	$\frac{\text{Sales}}{\text{Fixed assets}}$

Table 3: Descriptive Statistics

Panel 1: Initial Sample of 1100 Files

	N		Mean	Median	Std. Deviation	Minimum	Maximum
	Valid	Missing					
R1	1101	0	,0486	,0000	,13888	-,30	2,22
R2	1101	0	1,8578	1,1616	3,21661	,00	38,66
R3	1101	0	1,2506	,7222	2,78775	-,33	38,66
R4	1101	0	,3384	,0000	6,76445	-2,73	218,78
R5	1101	0	16,4330	3,7069	62,31644	,00	1143,97
R6	1101	0	,4246	,1084	1,61192	-,81	24,00
R7	1101	0	1,7075	1,4853	26,13615	-503,58	353,28
R8	1101	0	2,7313	1,6582	18,20498	-508,35	171,71
R9	1101	0	,6269	,6396	,33071	,00	4,12
R10	1101	0	,0985	,0113	,16847	,00	1,92
R11	1101	0	2,4917	,0392	28,87212	,00	528,75
R12	1101	0	31,8619	1,5233	343,49391	-869,60	9044,70
R13	1101	0	-55,9104	,0000	1878,21829	-62320,79	127,25
R14	1101	0	,2621	,0000	5,08803	-,99	162,31
R15	1101	0	-,1274	,0229	3,16215	-96,00	6,14
R16	1101	0	-,1276	,0547	4,04111	-129,00	2,13
R17	1101	0	,0489	,0276	,18273	-3,34	1,29
R18	1101	0	,3713	,0903	2,97614	-15,76	57,85
R19	1101	0	7,3586	1,1348	67,03061	-166,53	1489,00
R20	1101	0	,7605	,9699	,88433	-21,03	4,41
R21	1101	0	,3359	,0764	2,42056	,00	68,00
R22	1101	0	,0500	,0199	,12317	-,01	2,00
R23	1101	0	1,6381	1,0671	3,08115	,00	40,00
R24	1101	0	23,5883	3,5805	105,03824	,00	1825,30

Panel 2: Clean Sample of 1028 Files

	N		Mean	Median	Std. Deviation	Minimum	Maximum
	Valid	Missing					
R1	1028	0	,0490	,0000	,13938	-,30	2,22
R2	1028	0	1,8023	1,1595	3,05007	,00	38,66
R3	1028	0	1,1831	,7141	2,54868	-,33	38,66
R4	1028	0	,0999	,0000	1,32264	-2,73	41,09
R5	1028	0	,3827	,1093	1,36529	-,56	24,00
R6	1028	0	1,5117	1,5138	26,39593	-503,58	353,28
R7	1028	0	3,0154	1,6656	7,26025	-64,75	61,35
R8	1028	0	,6247	,6434	,29719	,00	2,86
R9	1028	0	,1002	,0130	,17066	,00	1,92
R10	1028	0	1,9648	,0436	24,37959	,00	492,34
R11	1028	0	11,7772	1,5296	50,11959	-26,95	659,54
R12	1028	0	,4473	,0000	2,15259	-6,41	39,40
R13	1028	0	,0906	,0000	1,30852	-,99	41,09
R14	1028	0	,0036	,0235	,40970	-9,04	6,14
R15	1028	0	,0432	,0576	,31278	-7,34	2,13
R16	1028	0	,0490	,0274	,14367	-,75	1,29
R17	1028	0	,1943	,0898	1,01661	-7,48	8,77
R18	1028	0	5,0329	1,1156	53,01150	-17,14	1489,00
R19	1028	0	,7599	,9678	,91074	-21,03	4,41
R20	1028	0	,2847	,0809	1,34449	,00	34,72
R21	1028	0	,0502	,0209	,11140	-,01	1,43
R22	1028	0	1,4083	1,0598	1,84801	,00	22,61
R23	1028	0	15,2129	3,4569	46,59783	,00	556,00
R24	1028	0	15,2038	3,7870	53,30320	,00	828,60

Table 4: Normality One-Sample Kolmogorov-Smirnov Test

Panel 1: Healthy Group

Financial ratios	N	Normal Parameters (a,b)		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
R1	824	,0471	,13914	,366	,336	-,366	10,516	,000
R2	824	1,8085	2,81133	,266	,266	-,260	7,634	,000
R3	824	1,1991	2,38531	,304	,285	-,304	8,725	,000
R4	824	,0635	,31000	,351	,351	-,308	10,063	,000
R5	824	,4115	1,41601	,328	,293	-,328	9,405	,000
R6	824	2,0356	22,44531	,417	,324	-,417	11,957	,000
R7	824	2,9613	7,06329	,285	,230	-,285	8,189	,000
R8	824	,6031	,29586	,062	,062	-,029	1,774	,004
R9	824	,0895	,15542	,282	,239	-,282	8,105	,000
R10	824	,6231	2,93786	,416	,383	-,416	11,942	,000
R11	824	13,4465	55,22646	,353	,353	-,335	10,131	,000
R12	824	,4965	2,33166	,414	,414	-,385	11,878	,000
R13	824	,0520	,23676	,356	,356	-,303	10,228	,000
R14	824	,0113	,44021	,306	,269	-,306	8,793	,000
R15	824	,0451	,33956	,298	,236	-,298	8,552	,000
R16	824	,0569	,15167	,158	,158	-,146	4,522	,000
R17	824	,2279	1,07093	,254	,254	-,243	7,293	,000
R18	824	2,9684	8,02752	,333	,332	-,333	9,551	,000
R19	824	,7714	,97580	,399	,399	-,271	11,450	,000
R20	824	,2264	,85070	,395	,300	-,395	11,341	,000
R21	824	,0439	,10201	,332	,295	-,332	9,534	,000
R22	824	1,4917	2,00516	,228	,221	-,228	6,558	,000
R23	824	16,4226	50,29149	,372	,317	-,372	10,679	,000
R24	824	16,8410	58,92186	,388	,329	-,388	11,124	,000

a Test distribution is Normal.
b Calculated from data.

Panel 2: Risky Group

Financial ratios	N	Normal Parameters (a,b)		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
R1	202	,0568	,14126	,339	,323	-,339	4,815	,000
R2	202	1,7824	3,89500	,378	,378	-,330	5,376	,000
R3	202	1,1216	3,14479	,376	,376	-,357	5,339	,000
R4	202	,2493	2,91832	,423	,423	-,388	6,015	,000
R5	202	,2644	1,13862	,384	,384	-,351	5,463	,000
R6	202	-,6451	38,61683	,418	,337	-,418	5,938	,000
R7	202	3,2330	8,05614	,275	,190	-,275	3,911	,000
R8	202	,7139	,28477	,107	,107	-,079	1,520	,020
R9	202	,1435	,21713	,254	,189	-,254	3,616	,000
R10	202	7,4528	54,44129	,478	,478	-,446	6,787	,000
R11	202	5,0374	16,99915	,342	,342	-,289	4,860	,000
R12	202	,2349	1,14835	,419	,419	-,336	5,958	,000
R13	202	,2493	2,91323	,447	,447	-,390	6,355	,000
R14	202	-,0279	,24972	,232	,219	-,232	3,299	,000
R15	202	,0345	,16518	,170	,154	-,170	2,412	,000
R16	202	,0164	,10087	,134	,112	-,134	1,908	,001
R17	202	,0584	,74945	,220	,220	-,188	3,129	,000
R18	202	13,4944	118,34374	,485	,485	-,449	6,895	,000
R19	202	,7150	,58043	,307	,307	-,162	4,360	,000
R20	202	,5194	2,48962	,417	,345	-,417	5,932	,000
R21	202	,0754	,14148	,297	,263	-,297	4,222	,000
R22	202	1,0743	,91634	,138	,138	-,121	1,955	,001
R23	202	10,4171	26,59611	,348	,283	-,348	4,941	,000
R24	202	8,5991	15,69335	,292	,265	-,292	4,148	,000

a Test distribution is Normal.
b Calculated from data.

Table 5: Group Means

Ratios	Code	N	Mean	Std. Deviation	Std. Error Mean
R1	,00	826	,0471	,13891	,00483
	1,00	202	,0568	,14135	,00995
R2	,00	826	1,8072	2,80796	,09770
	1,00	202	1,7822	3,89486	,27404
R3	,00	826	1,1982	2,38237	,08289
	1,00	202	1,1215	3,14473	,22126
R4	,00	826	,0634	,30944	,01077
	1,00	202	,2492	2,91846	,20534
R5	,00	826	,4116	1,41438	,04921
	1,00	202	,2644	1,13829	,08009
R6	,00	826	2,0391	22,41881	,78005
	1,00	202	-,6450	38,61664	2,71706
R7	,00	826	2,9623	7,05638	,24552
	1,00	202	3,2328	8,05572	,56680
R8	,00	826	,6028	,29616	,01030
	1,00	202	,7141	,28507	,02006
R9	,00	826	,0897	,15551	,00541
	1,00	202	,1434	,21732	,01529
R10	,00	826	,6227	2,93441	,10210
	1,00	202	7,4529	54,44136	3,83048
R11	,00	826	13,4255	55,16137	1,91931
	1,00	202	5,0372	16,99936	1,19607
R12	,00	826	,4993	2,33091	,08110
	1,00	202	,2348	1,14838	,08080
R13	,00	826	,0518	,23630	,00822
	1,00	202	,2492	2,91341	,20499
R14	,00	826	,0115	,43979	,01530
	1,00	202	-,0284	,25000	,01759
R15	,00	826	,0452	,33929	,01181
	1,00	202	,0347	,16519	,01162
R16	,00	826	,0569	,15137	,00527
	1,00	202	,0166	,10049	,00707
R17	,00	826	,2274	1,06959	,03722
	1,00	202	,0588	,74966	,05275
R18	,00	826	2,9637	8,01834	,27899
	1,00	202	13,4943	118,34374	8,32664
R19	,00	826	,7708	,97464	,03391
	1,00	202	,7151	,58013	,04082
R20	,00	826	,2273	,85044	,02959
	1,00	202	,5194	2,48971	,17518
R21	,00	826	,0439	,10179	,00354
	1,00	202	,0757	,14164	,00997
R22	,00	826	1,4900	2,00318	,06970
	1,00	202	1,0742	,91636	,06448
R23	,00	826	16,3857	50,23608	1,74794

	1,00	202	10,4172	26,59625	1,87131
R24	,00	826	16,8191	58,85241	2,04774
	1,00	202	8,5990	15,69326	1,10417

00: corresponds to healthy group 01: corresponds to risky group

Table 6: Independent Samples Test of Means Differences

		Levene's Test for		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean	Std. Error	95% Confidence	
									Lower	Upper
R1	Equal variances assumed	1,809	,179	-,886	1026	,376	-,00969	,01094	-,03116	,01178
	Equal variances not			-,876	303,052	,381	-,00969	,01106	-,03145	,01207
R2	Equal variances assumed	,577	,448	,104	1026	,917	,02500	,23952	-,44502	,49501
	Equal variances not			,086	254,343	,932	,02500	,29094	-,54795	,59795
R3	Equal variances assumed	,001	,977	,383	1026	,702	,07668	,20014	-,31605	,46940
	Equal variances not			,325	260,133	,746	,07668	,23628	-,38859	,54194
R4	Equal variances assumed	12,506	,000	-1,791	1026	,074	-,18577	,10371	-,38927	,01773
	Equal variances not			-,903	202,106	,367	-,18577	,20562	-,59121	,21968
R5	Equal variances assumed	1,607	,205	1,374	1026	,170	,14715	,10712	-,06304	,35735
	Equal variances not			1,565	368,635	,118	,14715	,09400	-,03769	,33200
R6	Equal variances assumed	7,073	,008	1,296	1026	,195	2,68406	2,07121	-1,38024	6,74835
	Equal variances not			,949	235,110	,343	2,68406	2,82681	-2,88507	8,25318
R7	Equal variances assumed	1,776	,183	-,475	1026	,635	-,27055	,57009	-1,38924	,84813
	Equal variances not			-,438	281,097	,662	-,27055	,61769	-1,48644	,94533
R8	Equal variances assumed	5,756	,017	-4,823	1026	,000	-,11130	,02308	-,15659	-,06602
	Equal variances not			-4,936	315,750	,000	-,11130	,02255	-,15567	-,06694
R9	Equal variances assumed	18,146	,000	-4,037	1026	,000	-,05369	,01330	-,07978	-,02759
	Equal variances not			-3,310	253,525	,001	-,05369	,01622	-,08563	-,02174
R10	Equal variances assumed	45,343	,000	-3,590	1026	,000	-6,83023	1,90265	-10,56375	-3,09671
	Equal variances not			-1,782	201,286	,076	-6,83023	3,83184	-14,38593	,72547
R11	Equal variances assumed	11,594	,001	2,136	1026	,033	8,38829	3,92723	,68197	16,09462
	Equal variances not			3,709	982,199	,000	8,38829	2,26149	3,95039	12,82620
R12	Equal variances assumed	5,025	,025	1,566	1026	,118	,26449	,16884	-,06683	,59581
	Equal variances not			2,310	649,440	,021	,26449	,11448	,03969	,48929
R13	Equal variances assumed	13,921	,000	-1,924	1026	,055	-,19735	,10258	-,39864	,00393
	Equal variances not			-,962	201,647	,337	-,19735	,20515	-,60187	,20716
R14	Equal variances assumed	,006	,937	1,239	1026	,216	,03984	,03215	-,02325	,10292
	Equal variances not			1,709	544,394	,088	,03984	,02331	-,00596	,08563
R15	Equal variances assumed	,471	,493	,429	1026	,668	,01053	,02456	-,03766	,05873
	Equal variances not			,636	658,801	,525	,01053	,01657	-,02200	,04306
R16	Equal variances assumed	7,932	,005	3,597	1026	,000	,04033	,01121	,01833	,06233
	Equal variances not			4,574	452,039	,000	,04033	,00882	,02300	,05765
R17	Equal variances assumed	1,442	,230	2,116	1026	,035	,16858	,07966	,01227	,32490
	Equal variances not			2,612	425,261	,009	,16858	,06455	,04170	,29547
R18	Equal variances assumed	23,653	,000	-2,537	1026	,011	-10,53058	4,15006	-18,67415	-2,38701
	Equal variances not			-1,264	201,452	,208	-10,53058	8,33131	-26,95834	5,89717
R19	Equal variances assumed	,007	,933	,779	1026	,436	,05569	,07150	-,08462	,19599
	Equal variances not			1,049	514,528	,295	,05569	,05307	-,04857	,15994
R20	Equal variances assumed	9,997	,002	-2,777	1026	,006	-,29210	,10519	-,49851	-,08569
	Equal variances not			-1,644	212,592	,102	-,29210	,17766	-,64230	,05809
R21	Equal variances assumed	8,983	,003	-3,654	1026	,000	-,03176	,00869	-,04881	-,01470
	Equal variances not			-3,003	253,998	,003	-,03176	,01058	-,05259	-,01093
R22	Equal variances assumed	7,594	,006	2,876	1026	,004	,41576	,14454	,13212	,69940
	Equal variances not			4,379	709,288	,000	,41576	,09495	,22935	,60217
R23	Equal variances assumed	6,944	,009	1,633	1026	,103	5,96845	3,65464	-1,20297	13,13987
	Equal variances not			2,331	594,494	,020	5,96845	2,56068	,93937	10,99752
R24	Equal variances assumed	10,040	,002	1,967	1026	,049	8,22005	4,17809	,02147	16,41863
	Equal variances not			3,533	1020,419	,000	8,22005	2,32646	3,65485	12,78525

Shaded area is to consider

Table 7: Results for Non Cash-Flow and Cash-Flow NNs models (In and Out-of-Sample)

Panel 1: Non Cash-Flow NNs Models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 [21 2]	15.5%	84.5	79.6%	15.7%	84.3%	79.3%
Net_01 [21 8 2]	15.2%	84.8	66.75%	15.5%	84.5%	78.66%
Net_02[21 10 8 2]	5%	95%	98.1%	2%	98%	67%
Net_03 [21 10 10 8 2]	6%	94%	73.25%	7%	93%	68.3
Net_03 [21 10 10 10 2]	15.4%	84.6%	70.5%	15.24%	84.76%	72.6%
Net_03 [21 12 12 12 2]	**1.9%**	**98.1**	**97.1%**	**0.3%**	**99.7%**	**71%**
Net_04 [21 12 12 12 8 2]	3%	97%	95.12%	3.1%	96.9%	68.33%

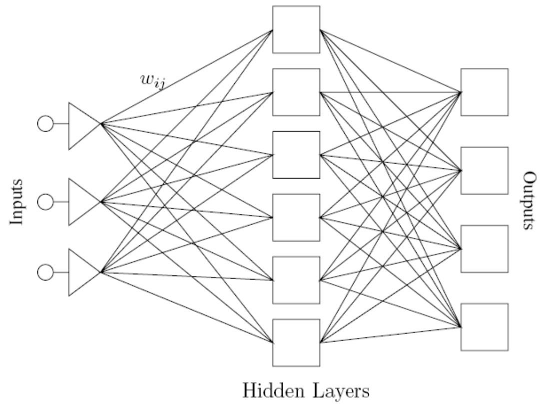
Panel 2: Cash-Flow NNs Models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 [24 2]	10.7	89.3%	85.62%	11.5%	88.5%	50.33%
Net_01 [24 8 2]	15.4	84.6 %	79.6%	15.6%	83%	75.66%
Net_02 [24 10 8 2]	**3.8%**	**96.2%**	**97.25%**	**4%**	**96%**	**90%**
Net_03 [24 10 10 8 2]	3%	97%	96.75%	4%	96%	71%
Net_03 [24 10 10 10 2]	2%	98%	79.5%	15.16%	84.84	51.6%
Net_03 [24 12 12 12 2]	0.6%	99.4%	98.25%	1.8%	98.2%	67.33%
Net_04 [24 12 12 12 8	0.5%	99.5%	81%	16%	84%	42.66%

Panel 3: Full Information NN Models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 [27 2]	9	91	88.37%	9.2	90.8	71.33%%
Net_01 [27 8 2]	1.8	98.2	98.75%	1.66	98.34	66.66%
Net_02 [27 10 8 2]	**0.72**	**99.28**	**99.5%**	**0.9**	**99.1**	**95.3%**
Net_03 [27 10 10 8 2]	1	99	99%	2	98	92.33%
Net_03 [27 10 10 10 2]	0.78	99.22	98.12%	1.25	98.75	66.66%

Figure 1: A Generic Feed-Forward Network with a Single Hidden Layer



Source: Daniel Berg (2005, 11)

Figure 2: Curves of the Mean Square Error (training) for the Non Cash-Flow NNs Model (with three hidden layers: Net_03 [21 12 12 12 2])

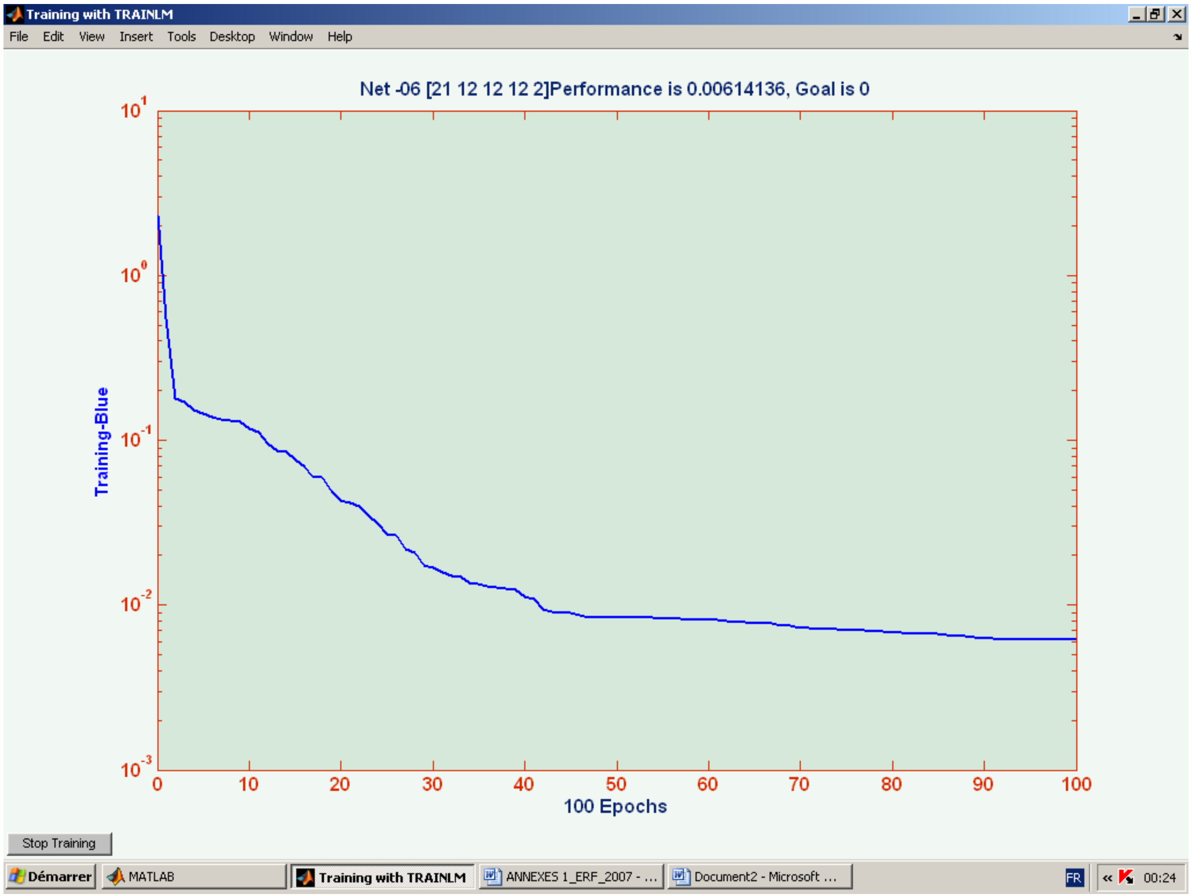


Figure 3: Curves of the Mean Square Error (training) for the Cash-flow NNs models (with two hidden layers: Net_02 [24 10 8 2].

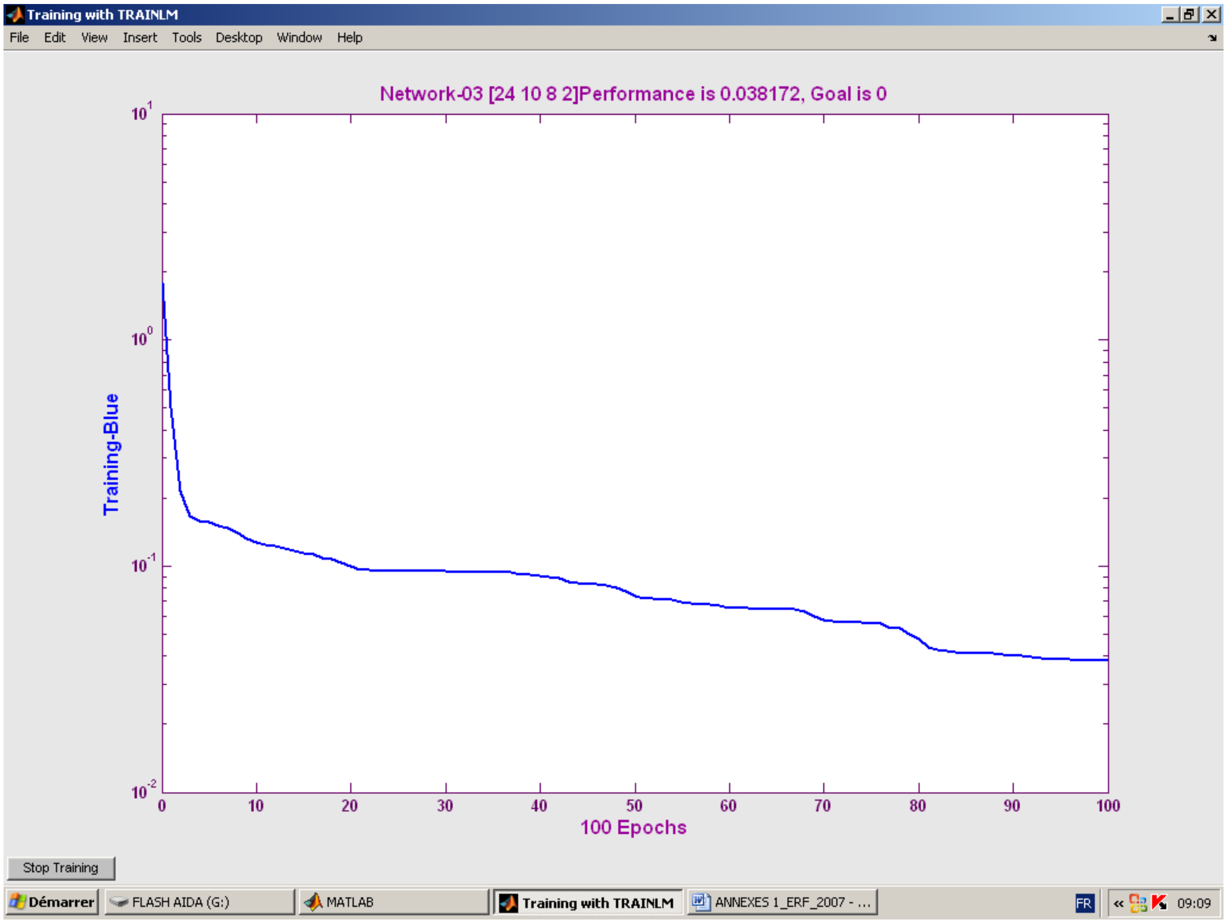


Figure 4: Curves of the Mean Square Error (training) for the Full Information NN models (with two hidden layers: Net_02 [27 10 8 2])