THE VALUATION OF GOVERNMENT GUARANTEES PROVIDED FOR MUNICIPALITIES

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCINECES

OF

MIDDLE EAST TECHNICAL UNIVERSITY

BY

MEHMET ESAT MERT

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR

THE DEGREE OF MASTER OF SCIENCE

IN

INDUSTRIAL ENGINEERING

July 2015

Approval of the Thesis

THE VALUATION OF GOVERNMENT GUARANTEES PROVIDED FOR MUNICIPALITIES

Submitted by **MEHMET ESAT MERT** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering Department, Middle East Technical University** by,

Prof. Dr. Gülbin Dural Ünver ___________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Murat Köksalan ___________________
Head of Department,
Industrial Engineering Dept., METU

Assoc. Prof. Dr. Serhan Duran ___________________
Supervisor, **Industrial Engineering Dept., METU**

Assoc. Prof. Dr. Cem İyigün ___________________
Co-Supervisor, **Industrial Engineering Dept., METU**

Examining Committee Members:

Assist. Prof. Dr. Mustafa Kemal Tural ___________________
Industrial Engineering Dept., METU

Assoc. Prof. Dr. Serhan Duran ___________________
Industrial Engineering Dept., METU

Assoc. Prof. Dr. Cem İyigün ___________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Melih Çelik ___________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. M. Alp Ertem ___________________
Industrial Engineering Dept., Cankaya University

Date: 23.07.2015

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name Last name: MEHMET ESAT MERT

Signature:…………………………….

ABSTRACT

THE VALUATION OF GOVERNMENT GUARANTEES PROVIDED FOR MUNICIPALITIES

Mert, Mehmet Esat

M.S., Department of Industrial Engineering

Supervisor: Assoc. Prof. Dr. Serhan Duran

Co-Advisor: Assoc. Prof. Dr. Cem İyigün

July 2015, 77 pages

Credit risk is defined as the risk of portfolio value variations due to unforeseeable fluctuations in the credit quality of a party in a financial contract. The operations that create receivable and contingent liability are the basic sources of credit risk. Credit risk models are needed in order to quantify the risk related to these sources better and minimize them by monitoring regularly. Although credit risk models are widely used in private sector, there are also usage areas for various operations of the government especially in public debt operations.

In public debt management, credit risks are mainly arised from Treasury guarantees, on-lent credits and other Treasury receivables. In this regard, government repayment guarantees and on-lent credits provided for municipalities are basic contingent liabilities of the government. These guarantees turn into liabilities in case of municipality defaults. In order to prevent the unexpected distress due to mentioned contingent liabilities and meeting the cash needed without creating pressure on government borrowing, a comprehensive credit risk management is a requirement. Therefore accurate guarantee premium pricing of guarantees and on-lent credits provided for municipalities is our focus in this study.

In the first part of the study, Logistic Regression and Artificial Neural Networks (ANNs) are utilized to estimate the default probabilities of several municipalities in Turkey. Then the cost of the insurance for guaranteed and on-lent credits provided to the municipalities is computed by relating the guarantee premium to several tools such as Credit Default Swap, Interest Rate Difference and Expected Loss.

Keywords— Default Probability, Government Guarantee Premium, Artificial Neural Networks (ANNs), Credit Default Swap (CDS) Pricing.

ÖZ

BELEDİYELERE SAĞLANAN HAZİNE GARANTİLERİNİN FİYATLANDIRILMASI

Mert, Mehmet Esat

Yüksek Lisans, Endüstri Mühendisliği

Tez Yöneticisi: Doç. Dr. Serhan Duran

Tez Yönetici Yardımcısı: Doç. Dr. Cem İyigün

Temmuz 2015, 77 sayfa

Kredi riski, bir finansal anlaşmanın tarafının kredi kalitesinde beklenmeyen dalgalanmalardan kaynaklanabilecek portföy değeri değişimi riski olarak tanımlanır. Alacak ve koşullu yükümlülük oluşturan operasyonlar kredi riskinin temel nedenleridir. Bu kaynaklarla ilgili riski ölçmek ve düzenli izleyerek minimuma indirmek için kredi riski modellerine ihtiyaç duyulur. Her ne kadar, kredi riski modelleri özel sektörde yaygın olarak kullanılsa da, devletin çeşitli işlemleri için özellikle kamu borç operasyonlarında da kullanım alanları mevcuttur.

Kamu borç yönetiminde kredi riski temel olarak Hazine garantilerinden, ikrazlı kredilerden ve diğer Hazine alacaklarından kaynaklanır. Bu kapsamda, Belediyelere sağlanan Hazine geri ödeme garantileri ve ikrazlı krediler devletin en temel koşullu yükümlülüklerindendir. Belediyenin temerrüde düşmesi durumunda bu garantiler yükümlülüklere dönüşürler. Devlet borçlanmasında bahsedilen koşullu yükümlülüklerden kaynaklı beklenmedik sıkıntıları önlemek ve baskı yaratmadan gerekli nakiti sağlamak için, kapsamlı bir kredi risk yönetimi

ihtiyaçtır. Bu sebeple, belediyelere sağlanan garantiler ve ikrazlı krediler için hassas bir garanti primi fiyatlandırması bu çalışmanın odak noktasıdır.

Çalışmanın ilk aşamasında, belediyelerin temerrüt olasılıklarını tahminlemek için Lojistik Regresyon (LR) ve Yapay Sinir Ağları (YSA) kullanılmıştır. Daha sonra, belediyelerin tahminlenen temerrüt olasılıkları kullanılarak ve garanti primini Kredi Temerrüt Takası, Faiz Oranı Farkı ve Beklenen Kayıp gibi methodlarla ilişkilendirerek belediyelere sağlanan garantili ve ikrazlı krediler için sigorta maliyeti hesaplanmıştır.

Anahtar Kelimeler: Temerrüt Olasılığı, Hazine Garanti Primi, Yapay Sinir Ağları (YSA), Kredi Temerrüt Takası (KTT) Fiyatlaması.

To My Family

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my academic supervisors Assoc. Prof. Dr. Serhan Duran and Assoc. Prof. Dr. Cem İyigün for their guidance and criticism throughout the study. Beside my academic advisors, I would like to thank Dr. Emre Balibek for his valuable advices and support during the study.

Besides my advisors, I wish to express my appreciation to the rest of my thesis committee for their valuable comments and reviews.

Also, I would like to thank Mr. Fatih Kuz, Mr. Özdemir Yalçın, Ms. Gökçe Demirdere and Ms. Tuğba İldaş from Undersecretariat of Treasury for their significant support.

Last but not least, I am thankful to my family for their support during my whole life. Special thanks to my dear Hazel, whose trust and support has always been my source of motivation.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ABBREVIATIONS

A-IRB:	Advanced Internal Rating Based Approach
AIP:	Annual Investment Program
ANN:	Artificial Neural Network
AUC:	Area Under Curve
BoD:	Board of Directors
CDS:	Credit Default Swap
CF:	Cash Flow
CPI:	Consumer Price Index
CRD:	Credit Risk Department
DP:	Default Probability
EAD:	Exposure At Default
EL:	Expected Loss
FA:	Factor Analysis
FAD:	Financial Analysis Department
FDI:	Foreign Direct Investment
F-IRB:	Foundation Internal Rating Based Approach
FYE:	Financial Year End
GDFER:	General Directorate of Foreign Economic Relations
GDP:	Gross Domestic Product
GDPF:	General Directorate of Public Finance
IFI:	International Financial Institution
IRD:	Interest Rate Difference
IRS:	Interest Rate Spread
IT:	Information Technologies

LGD:	Loss Given Default
LR:	Logistic Regression
MAE:	Mean Absolute Error
MAPE:	Mean Absolute Percentage Error
MPE:	Mean Percentage Error
MSE:	Mean Squared Error
MoD:	Ministry of Development
PCA:	Principal Component Analysis
PD:	Probability of Default
PDE:	Partial Differential Equations
PFD:	Project Finance Department
PEA:	Project Executing Agency
PPP:	Public-Private Partnership
ROC:	Receiver Operating Characteristics
RWA:	Risk Weighted Asset
SA:	Standardized Approach
SME:	Small and Medium Enterprises
SPV:	Special Purpose Vehicle
S&P:	Standard and Poor’s
UoT:	Undersecretariat of Treasury
WCDR:	Worst Case Default Rate

Currencies

EUR:	Euro
TL:	Turkish Lira
USD:	US Dollar

CHAPTER 1

INTRODUCTION

Lending money is risky since there is no guarantee that you will get all your money back. If the borrower defaults, you will face losses in your portfolio. These are typical situations in which credit risk manifests itself. In accordance with the Basel Accord (a global regulation organization for financial institutions) credit risk is one of the three basic risks an institution faces during operations (the two other risks are market risk and operational risk) and the probability of default is the most important component in credit risk. As the latest financial crises have shown us, we need to understand and control the credit risk properly.

In order to ensure the repayments of the financing, guarantee agencies provide financial guarantees to the lenders and investors. By the help of this guarantee mechanism, investors and lenders are attracted to invest into risky operating environment, foreign direct investments are promoted and the borrower gains access to finance with better terms by benefiting guarantor's credibility.

Countries supply various types of guarantees and on-lent credits to provide finance for the local governments, governmental institutions and small and medium enterprises (SMEs) in order to support projects related to infrastructure, regional development, transportation, energy generation, etc. However, delays in the repayment of guaranteed or on-lent credits increase the cash needs which in return may negatively affect the terms of governmental borrowing. Besides, any case of default damages the country's reputation in international financial market. These transactions create debt-credit relationship and contingent liabilities which are the main credit risk sources for the government.

Committed loan amounts with government guarantee has an increasing trend although there exists a decrease related to the economic crisis after 2009. Government guarantees and on-lent credits are accounted as extra budgetary transactions and are not included in central government debt statistics since they are contingent liabilities (D.A. Memiş, V.G. Karadağ, H. Bingöl, 2012). These guarantees turn into liability in case the borrowing institution defaults. Thus, the management of the counterparty risk for guaranteed and on-lent credits is important in terms of ensuring the budget balance and the effectiveness of the cash management. In order to quantify the risk related to these sources better and minimize them by monitoring regularly, credit risk models are needed.

An in-depth credit risk management enables one to handle several issues such as what would be the estimated default probability (and recovery rate in case of default) of the institutions, whether the guarantee will be provided or not in the light of this probability, if provided how much it will cost and the amount to be allocated in the risk account which will be activated in case of default.

Local governments also can access to low cost financing with guarantees provided by the guarantee agencies. The evaluation of local government's potential has become one of the main issues worldwide since municipalities' responsibility increases day by day for providing main services to the citizens. In today's world, decision-making is decentralized to local governments. Thus, the financial performances of the municipalities are very important in terms of meeting their financial obligations and satisfying its services to its tax payers. In Turkey, municipalities access to low cost financing for their infrastructure projects with guarantees and on-lent credits provided by Undersecretariat of Treasury in Turkey (UoT). This guarantee is a contingent liability for UoT as mentioned above. Whenever an institution cannot pay an installment, UoT pays the defaulted amount instead of the borrowing institution. Then, UoT restructures and reclaims the paid amount which creates receivable for UoT. These receivables are comprised mostly of guaranteed loans provided to the local government for the years of 2012, 2013 and 2014 (Data on Treasury Receivables Retrieved from: http://www.treasury.gov.tr). In order to manage the counter party risk of this transaction which creates the entire burden from this special type of mechanism, a credit risk model specific to the municipalities needs to be developed.

We have aimed to contribute to literature by estimating default probabilities (also referred to as probability of default) of municipalities in Turkey more precisely using Artificial Neural Networks (ANNs). By utilizing estimated probabilities to calculate the fair guarantee premium of the guaranteed and on-lent credits provided, we wanted to show the benefit of the accurate calculation for the sake of beneficiary.

We offer a method to calculate the guarantee premium and show how much the UoT should seek in order to extend its guarantee. After these calculations, the capital requirement for the portfolio consisting of municipality loans is found. Calculating default risk decreases two main losses. One is the borrowing cost which is caused by the capital deficit in the risk account. The other is the opportunity cost of not being able to invest excess money due to overestimating the default risk. Beside, we reveal which variables are significant in terms of probability of default calculation and the amount of the guarantee premium.

Then we question the limit applied on the guarantee premium in the current legislation. We compare the results with the actual costs and suggest an additional limit by interpreting Basel Accord regulations. Lastly, we apply stress testing to our models by tuning our main parameters. By doing so, we see how the guarantee premium calculated and accumulated in the risk account reacts in different environments with different scenarios which is simply given configuration of different parameters and variables of the models.

In our study, first the default probabilities of the municipalities are estimated by considering their financial, debt-related, economic and administrative variables. ANNs and Logistic Regression are used to estimate the probabilities. Then the cost of insurance for the guaranteed and on-lent credits provided to the municipalities is computed with relating the guarantee premium to some benchmarks which are CDS, IRD and EL pricing using the estimated default probabilities of the municipalities. Lastly, stress testing is applied to our models based on different scenarios.

CHAPTER 2

LITERATURE REVIEW

Credit risk assessment is one of the crucial and essential data mining topics. According to Basel Accord, credit risk has two components which are default risk and credit deterioration (quality) of a counterparty. Default risk is associated with probability of default (PD). PD can be estimated by using rating or by models of default.

The figure showing the classified methods for estimating of PD can be found below:

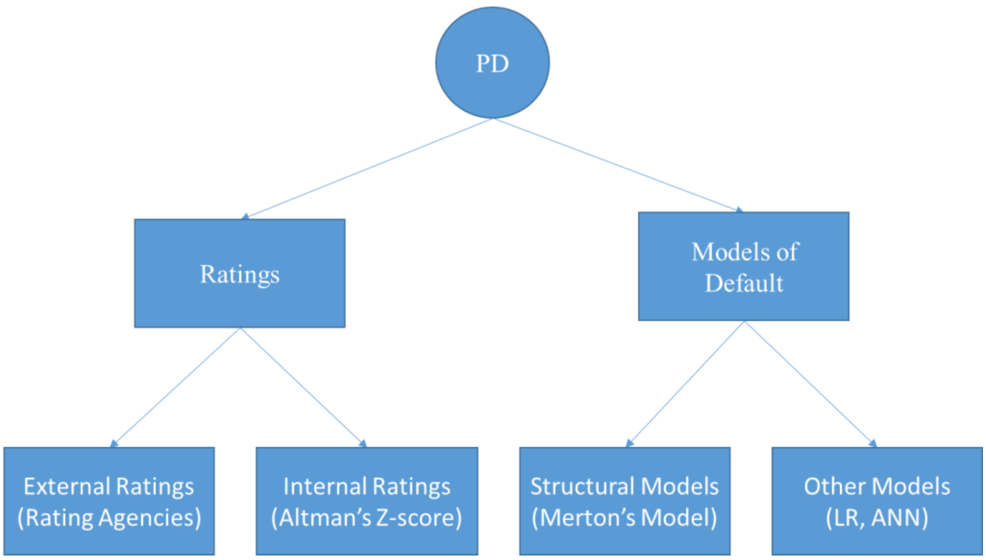


Figure-2.1: Methods for Estimating PD

The ratings to be used in estimating PD can be provided externally or internally. External rating are ratings obtained from third parties, typically rating agencies such as S&P, Moody's and Fitch. However these ratings are accessible for certain or large corporate clients. Also, the ratings are obtained on demand so there might not exist rating for the related counterparty. Thus, some financial institutions need to use internal ratings obtained by internal proprietary methods.

Altman's Z-score which is introduced in 1968 using discriminant analysis, has extreme importance is this field. It is a financial distress index using internal ratings. Altman used linear combination of some ratios with discriminant function to evaluate the performance of ratio analysis. By taking account of 33 defaulted and 33 non-defaulted companies, the model he developed classified 95 % of the observations correctly.

Models of default can be structural or non-structural. In structural model of default, default can happen when the asset of the counterparty reaches a sufficiently low level with respect to its liabilities or any other parameter.

Merton's model is one of the most famous structural models. In 1997, Merton developed his model defining default as a stochastic variable representing the case where some asset value falls below a given threshold such as liabilities. This model is the prototype of this class and there are many extensions proposed in the literature such as KMV (Kealhofer, McQuown and Vasicek), a research driven company, and Credit Metrics models. These models are sometimes called as threshold models. Merton's model has strong linkage with famous Black and Scholes model in option pricing.

Non-structural models of default are rather sophisticated models. In the literature, there are various methods classified as non-structural for default risk estimation. These methods mainly include logistic regression (Bolton, 2009; Wiginton, 1980), probit regression (Grablowsky & Talley, 1981) and artificial neural network (Jensen, 1992; West, 2000). Among these methods, logistic regression is reputed to be the most popular approach and has been widely used. Beside, Artificial Neural Networks (ANNs) models have high accuracy but they require modelling skills - for instance, to design proper network topologies - and it is difficult to explain their outcomes.

Cames and Hill (2000) wanted to show if the underlying probability distribution of dependent variable affects the prediction ability. They compared the logistic, probit, weibit and gombit models and concluded that they are statistically not different.

Tam and Kiang (1992) used neural networks and extended the backpropagation by considering misclassification costs. Then they compared the new algorithm with logistic regression, linear classifier, decision trees and *k*-nearest neighbor in terms of predictive accuracy, robustness and adaptability. The results showed that the neural network is a promising method.

Kiviluoto (1998) compared self-organizing maps (SOM), which is a type of neural network, with linear discriminant analysis. The study concluded that neural network outperforms discriminant analysis.

Pompe (1997) compared classification tree with logistic regression and neural network. The results indicated that decision tree is better than logistic regression but it does not outperform neural networks in terms of prediction ability.

Other than the studies listed above, there are several models used to predict financial situation in the private sector. These models are applied rarely in the public sector. The main reason is that the accrual accounting variables were started to be published only recently by most of municipalities (Blum, 1974). Thus, accessing financial ratios of the municipalities is more challenging than of the companies. In addition, some application differences are expected in the models used in the public sector due to distinct characteristics of the financial indicators and their effects. For instance, increased profitability is interpreted as an indication of efficiency in the private sector corporations, but it has not the same meaning for municipalities. It can be interpreted as high taxes imposition since the municipalities should have non-profit characteristics. In a similar manner, high debt position may not be interpreted as the municipality is likely to be defaulted since the central government allocates funds for municipalities to reduce the liquidity risk.

There are different heuristic approaches used in the literature such as statistical modeling and financial statement analysis to evaluate municipality’s credit risk and default probabilities. Most of these studies were conducted in US since their accounting and reporting system is relatively more demanding.

Kleine et al. (2003) examined the current models to evaluate the efficiency of local governments. In this study nine variables were used, weights were assigned to these variables and an alternative model was constructed for some of the Michigan local governments. The results showed that the alternative model outperformed the current system of Michigan.

Jones and Walker (2007) investigated the reasons for default of local governments by constructing a statistical model. They found that the probability of default is positively correlated with the number of revenue items, composition of revenue and number of people served.

Hajek (2010) used neural networks to construct credit rating model for US municipalities. He divided the variables of the municipalities into four categories which are economic, financial, debt related and administrative. Classification accuracies are studied for the different number of classes.

Cohen et al. (2011) construct a model to assess the financial situation of local governments in Greece. In this study, simulation analysis is used based on accrual financial data collected from 360 municipalities. The results showed that the employed model classifies failed municipalities correctly with respect to the benchmark used by the government.

After evaluation of the default probabilities of the municipalities, the guarantee premiums are calculated in our study. A guarantee premium is charged by the guarantor to prevent arbitrage in the system. It can be interpreted as the price of a Credit Default Swap (CDS) which is a bilateral contract in which one party (protection seller) is paid a fee for taking the responsibility of a contingent liability by the other party (the protection buyer) tied to the credit event of a indicated entity. The credit event in this case would be default and the reference security would be the Bank loan. The protection buyer is Municipality and the protection seller is Treasury. The value of the CDS represents the amount that Treasury would need to fund the hedge such that once the hedge was funded there would be enough money in the hedge to pay off if Municipality default, and zero in the hedge if Municipality is not in default. Thus, a risk-free liability is equal to the sum of a risky liability and a guarantee premium.

Bland and Yu (1987) studied on 1,139 bonds issued in 1985 and found that the net gain which is equivalent to the cost of borrowing minus the guarantee fee is positive and it is negatively correlated with credit ratings. Merton (1990) applied option pricing theory using 10 corporate bonds. He defined the implied guarantee value of bonds as the difference between the market price and risk-free price. Risk-free price is estimated by discounting cash flows using Treasury rate on bonds and notes on the specific date. This study was accepted as the principles of guarantee valuation.

There is limited number of studies looking at pricing of CDS. Duffie (1999) has one of the first attempts to price CDS but the model is not tested against CDS market data. Hull and White (2000) analyzed effects of recovery rate on CDS prices in a similar methodology but, again the model is not directly tested against market data. According to their study, if the recovery rates used both for calculating default probabilities and prices are the same, its effect is little when the recovery rate is assumed between 50% and 20%. In an extension study, Hull and White (2001) examined the default risk of the protection seller which is the guarantor in our case. They showed that the effect of seller’s default risk on the CDS price is dependent on credit quality and the correlation of default probabilities of reference entity and the seller. When correlation converges to zero, the effect of the seller’s default risk also converges to zero.

Aunon-Neri (2002) investigated the explanatory variables in CDS price and concluded that having a rating is the most explanatory source on credit risk among the other variables such as interest rates, bond spreads, stock prices, asset volatility and etc.

Hull, Pedrescu and White (2004) evaluated the negative announcements by rating agencies such as negative outlook and downgrade and they found that these announcements affect the CDS prices.

Schurman (2010) used CDS as a tool to value loan guarantee via no-arbitrage principle. He derived the value of CDS with replicating by trading in the underlying risky asset and a risk-free asset. The results were compared with the difference in interest rates of the risky loan and risk-free loan.

In the comparison table below, the contribution of our thesis to the literature is represented.

Table-2.1: Comparison Table of Thesis Contribution and Existing Literature

Description of Work	**Existing**	**New**
Estimating Default Probabilities of Municipalities	X	
Comparison of Parametric and Non-parametric Prediction Methods for Estimating Default Probabilities of Municipalities		X
Calculating Guarantee Premium	X	
Calculating Guarantee Premium of Municipalities Combined by the Estimated Default Probabilities		X

CHAPTER 3

MOTIVATION

In our study, we combine two issues as seen in the Figure-3.1 which are estimating PD and calculating guarantee premiums which generate capital collected for the risk account of UoT.

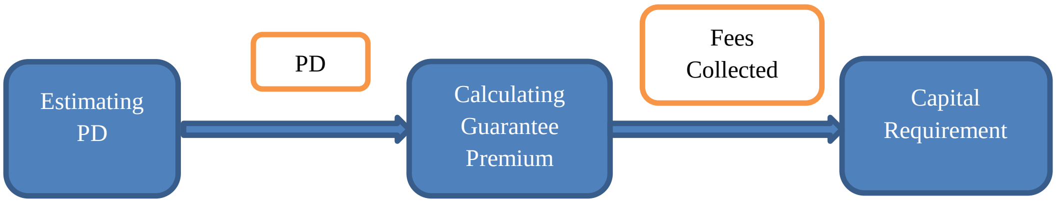


Figure-3.1: Study Background

Firstly, we need to mention the absence of study in the literature for estimating default probabilities of the municipalities by parametric and non-parametric prediction methods. Besides, at the best of our knowledge, there is no study on combining the estimated default probabilities by calculating fair guarantee premium for guaranteed or on-lent credits of municipalities.

Secondly, credit risk models are not only used to compute loss distributions, but also to calculate capital requirements for the guarantor (Carling, 2007). Suppose that two municipalities borrow loans backed by UoT guarantee from a Creditor. If the municipalities do not meet their payment obligations on time as seen in the Figure-3.2 below, UoT makes payment to the Creditor at $t=2$ for Municipality-1 and at $t=3$ for Municipality-2. In order to protect itself, UoT wants municipalities to pay a guarantee premium in exchange for UoT guarantee. The calculation of this premium is involved in PD values of municipalities and other parameter as we are going to discuss in further chapters.

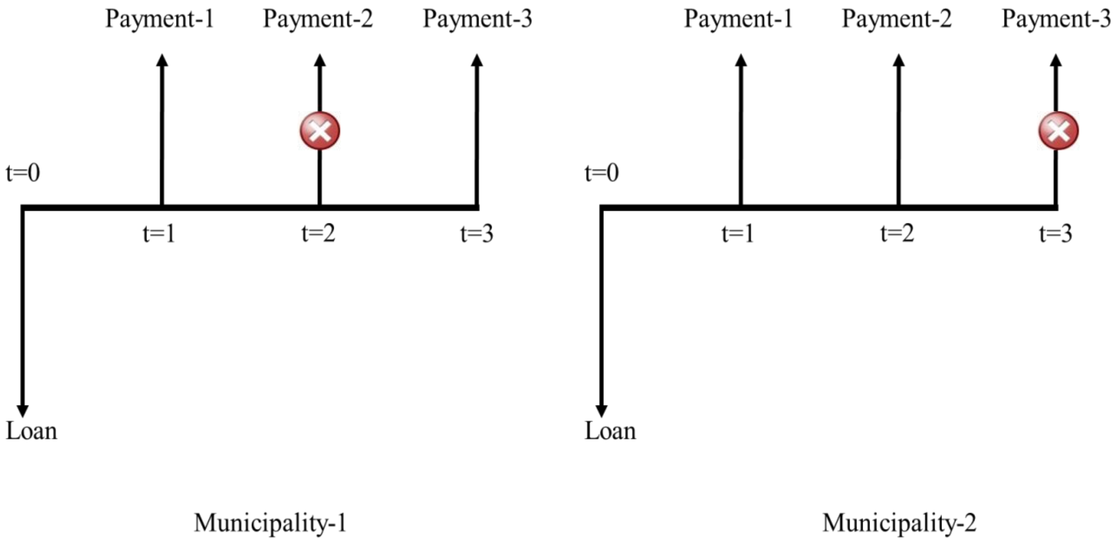


Figure-3.2: Cash-flow of Municipality Loans

Since UoT pays the loss caused from contingent liabilities only from the *risk account* created by the guarantee fees collected, the calculating of fair guarantee premium has an extreme importance. We can assume that in case of deficit in the risk account to meet the payment obligations due to the contingent liabilities, UoT faces the cost of borrowing to close the deficit. In case of excess capital in the risk account, UoT loses the opportunity to invest this amount and gain interest. The difference between the interest rates of borrowing with UoT guarantee and risk-free interest rate is defined as interest rate spread (IRS) in this study. It is assumed as 0 for UoT in this study which also assumes that the costs of deficit and excess capital in the risk account are same. Later on, in order to see the effects of different parameters on the guarantee premium, it is also accepted as 3.5% which is the current interest rate corridor applied by the Central Bank of Turkey on May, 2015.

Section 3.1 covers brief information about the UoT, and the process of providing foreign finance to municipalities are presented in order to provide an understanding on how our proposed models can help in functioning of the activities of UoT. Section 3.2 explains Basel Accord and its regulations which have significant importance to us. Section 3.3 is for study background where we explain the details of the background of the study.

3.1. Turkish Treasury and Providing Foreign Finance

The mission of the UoT is defined as managing public assets and liabilities, regulating, and implementing financial and economic policies and maintaining the coordination of international economic relations with all other stakeholders to contribute to the development of Turkey. There are several departments in UoT. Treasury Pay Office in General Directorate of Public Finance (GDPF) is responsible for equalization of the state revenues and expenditures by time and place. Other responsibilities of GDPF is risk management and back office activities.

Foreign economic relations are the responsibility of General Directorate of Foreign Relations (GDFR). In this directorate, the relations with other countries and international institutions and foreign borrowing activities are held. Thus, one of the duties of GDFR is to provide foreign financing to institutions or to manage the process of being guarantor for the publicly held projects.

Municipal projects also fall into GDFR's area of responsibility. From the perspective of UoT, credit risk of municipalities might be an issue when the UoT acts as a guarantor or provides on-lent credit. At this point, the repayment liability of the municipality becomes contingent liability for the UoT. Below, related legislation and foreign financing of municipalities' public projects are described.

3.1.1. Related Legislation

Foreign financing transactions in addition to domestic financing transactions of the Republic of Turkey are carried out in accordance with

a) The Law on Regulation Public Finance and Debt Management (Law No: 4749 dated March 28, 2002)

b) Regulation on Procedures and Principles of Providing Foreign Finance within Law No. 4749

c) Regulation on Permission for Providing Foreign Financing without Treasury Guarantee except Grant by Public Institutions and Monitoring the Provided Foreign Financing.

Institutions can use foreign finance for the purpose of financing their projects or for their budget via loans or bonds. For municipalities, UoT provides guaranteed and on-lent credits only for the project financing purposes with foreign credits.

The foreign financing of the infrastructure projects of the municipalities can be provided via three different ways;

(i) Via Treasury: Onlending of the financing from any external financing source,

(ii) Providing foreign financing with UoT guarantee and,

(iii) Without Treasury Guarantee.

In onlending, the borrower of the credit is UoT and UoT is responsible for the payment obligations to the creditor, whereas Project Executing Agency (PEA) has to repay UoT all the payments made to the creditor by UoT. The onlending terms and conditions are regulated by a separate onlending agreement signed between UoT and PEA.

Before explaining the guarantee extension to Municipalities, we need to explain the guarantee mechanism of UoT. UoT guarantees are specified in Article 3 and 4 of the Law mentioned above. There are 4 types of guarantees which are Repayment Guarantee, Investment Guarantee, Country Guarantee and Counter Guarantee.

Investment Guarantees are given within the scope of financing models of Public-Private Partnership such as Build-Operate-Transfer, Build-Operate, and transfer of operating rights, which are based on the related laws and limited by them. The Council of Ministers has the authority to extend Investment Guarantee.

Country Guarantee is used to ensure the external debt obligations of other countries by providing guarantee to foreign countries. Negotiations are conducted and finalized by UoT with respect to prior authorization of the Council of Ministers. Country Guarantee is not extended up until now.

Counter Guarantee is defined as the counter guarantee to the guarantee extended by a foreign finance institution for the financing provided from the international capital markets as borrower within the scope of guarantee program scheme of the foreign finance institution. Counter Guarantee can be given in favor of (i) state economic enterprises, special budget institutions, (ii) funds, (iii) state banks, investment and development banks, (iv) municipalities and various local institutions. Deputy Prime Minister in charge of UoT has the authority to extend Counter Guarantee.

Repayment Guarantee is the subject of this study and the term “UoT Guarantee” refers the Repayment Guarantee in the study. It is defined in the mentioned law as the guarantee for the repayment of external borrowing obtained from an external source of finance. It can be extended in favor of beneficiaries mentioned in Counter Guarantee. Deputy Prime Minister in charge of UoT has the authority to extend Counter Guarantee. In the Table-3.1, the details of guarantees are explained.

Table-3.1: Guarantees

Type	Coverage	Beneficiary	Approval Body
Repayment Guarantees	Guarantees for the repayment of external borrowing obtained from an external source of finance.	• State economic enterprises, special budget institutions , • Funds, • State banks, investment and development banks, • Municipalities and various local institutions	Deputy Prime Minister in charge of UoT
Investment Guarantees	Guarantees given within the scope of PPP models.	• SPV, • Related public institutions	Council of Ministers
Counter Guarantees	Guarantees given against the guarantees extended by an external source of finance.	• State economic enterprises, special budget institutions, • Funds, • State banks, investment and development banks, • Municipalities and various local institutions	Deputy Prime Minister in charge of UoT
Country Guarantees	Guarantees for repayment of financing obtained from any foreign financing source by foreign countries.	• Foreign countries	Council of Ministers

If extension of UoT guarantee is the method, the borrower is PEA itself whereas the UoT is guarantor of the payment obligations to the creditor. The credit agreement is negotiated by UoT. The terms and conditions of the guarantee are regulated by a separate guarantee agreement signed between UoT and PEA.

Municipalities also can provide foreign finance for their projects without UoT guarantee after getting permission from UoT.

3.1.2. Process of Providing Foreign Finance with Treasury Guarantee or Onlending

This process is quite similar for each institution but there are some differences for municipalities.

According to the definition of Ministry of Interior of Republic of Turkey, the municipality is a legal public entity organized to meet the needs of local population. Decision makers are elected by the voters and the main administrative units are Municipal Council, Municipal Executive Committee and Mayor.

Municipalities maintain projects in the sectors of construction, water and sewerage, solid waste, urban infrastructure, housing, social services, etc. The main financing sources of the municipalities are local taxes, tax share from general budget, non-tax revenues and borrowing.

Borrowing decision is made by the council. Foreign borrowings can be provided only with the permission of UoT and be used for the projects in Annual Investment Program (AIP) prepared by Ministry of Development (MoD). The financing can be provided by the involvement of UoT or by the contractor firm, which is the winner of the international competitive tender executed by the Municipality. In any case, the project needs to be already included in the AIP. The submission of the feasibility and other studies of the project to insert it into the AIP is the responsibility of PEA

When the project with enough budgets with specified foreign financing component to be utilized is included in the AIP, the Municipality applies to UoT for a foreign financing or international competitive tender bidding permit for its project. UoT asks the official views of MoD. After getting the response of MoD, various examinations are made at the Risk Management Unit in GDPF for the Municipality. The following criteria are needed to be met by Municipality:

- As of the application date, Municipality shall not have any overdue debt obligation to UoT,
- The projected revenues of Municipality in the repayment period of the loan need to be enough to meet the payment obligations of the loan and all other liabilities of the Municipality,
- According to Article 68 (d) of the Municipality Law (No: 5393), total debt stock of Municipality, subsidiaries and the companies with more than 50% of the share owned cannot exceed the total amount of final budget income updated by the revaluation rate determined in the Tax Procedural Law (No: 213). The ratio is 1.5 for the metropolitan municipalities. Nevertheless, the financing provided by multilateral development and investment banks and bilateral cooperations and EU funds are not included into the borrowing limit,
- The municipality is required to open a bank account and deposit some of its revenues to this account to be used in the repayments of the loan. This account need to be opened before the loan agreement is signed.

Followed by the favorable response of MoD and technical suitability according to the analysis made, the approval of the Deputy Prime Minister in charge of the UoT is obtained to provide the financing.

As mentioned above, UoT can provide foreign finance directly to the municipal projects. Financing projects with contractor of the International Competitive Tender is rare and affectless for the aim of this study. UoT, independent of the methods used (guarantee or onlending) secures the financing before the tender is implemented by Municipality. After tender process and commercial contract are signed, UoT contacts with potential lenders generally the International Financial Institutions (IFIs). The concessional untied governmental loans with favorable terms and conditions (and feasible with respect to the benchmark prepared by UoT) are preferred by UoT.

After negotiations are finished, the Loan Agreement between the Creditor and UoT (also the Municipality since it is the borrower) is signed. In addition, between UoT and Municipality a protocol regulating the conditions of guarantee or onlending including the guarantee premium to be charged to Municipality is signed. If the loan is on-lent to the Municipality, the borrower is UoT and the decision of Council of Minister is one of the conditions for the Loan Agreement to be effective. After all the conditions precedents of the Loan Agreement are met, disbursements start and debt service is paid during the repayment period. The flow chart of the process is given in Appendix A.

In any given fiscal year, the total amount of on-lent and guaranteed financing provided cannot exceed the guarantee and onlending limit set by the Annual Budget Law of that year (for 2014, the limit is USD 3 billion). Total committed loan amounts with UoT repayment guarantee and on-lent extended and the related annual limits between the years of 2005 and 2014 are given in the Figure-3.3.

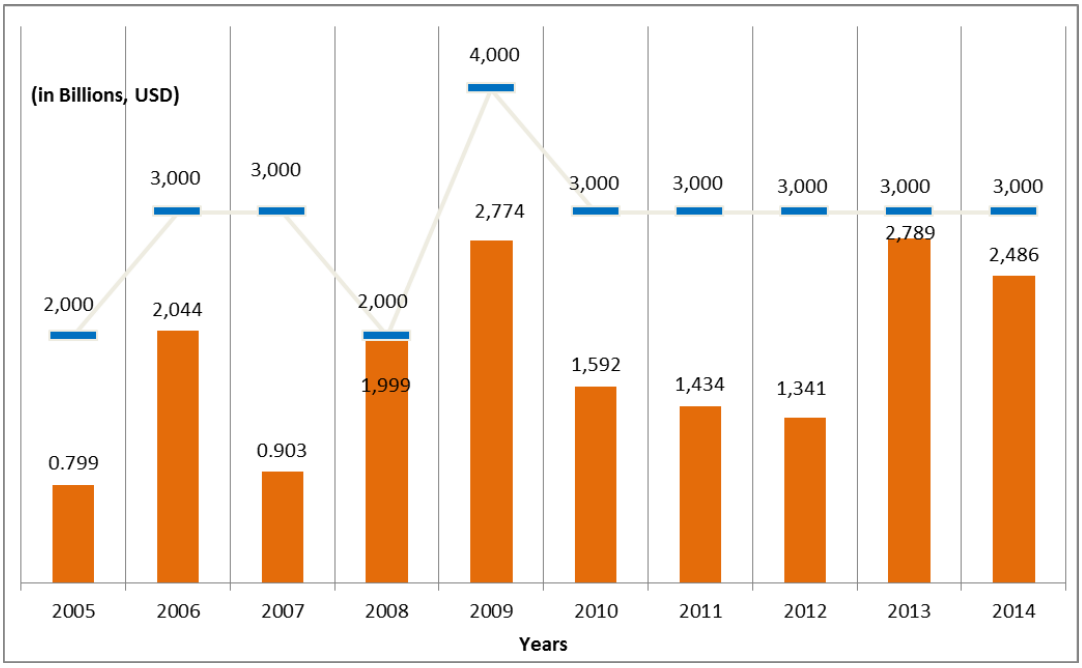


Figure-3.3: Committed Amounts and Limits

Treasury Repayment Guarantees can be extended up to 95% of the total liability if the creditor is not a foreign government institution. If so, the guarantee can be extended in full. The guarantee premium is regulated by the legislation and paid to UoT. It must be determined in the range of 0.1% to 1% of the guaranteed or on-lent amount.

3.2. Basel Accord

The ultimate aim of the study is to determine the capital requirement in the risk account of UoT. It is needed to be balanced since the excess money in the risk account has also a cost of opportunity. Basel Accord regulates these issues and these regulations need to be examined in our study, too.

As mentioned, the credit risk is one of the essential risks according to Basel Accord (Basel II and III) which is an important party on the subjects of credit risk and capital requirements. Credit risk contains both losses caused by default and losses due to credit quality variations of the counterparty on the domain of an internal or external rating system. Thus, the credit risk has two components which are default risk and credit deterioration.

Default risk is the risk of losing money in case of a default of the counterparty. At the end, the one might lose money totally or partially. Thus, the estimating of default probability is fundamental in terms of controlling the default risk.

Credit deterioration is linked to changes in credit quality of the counterparty which can be estimated by credit ratings. These ratings can be internal or external. It means ratings can be estimated by your own resources or they can rely on the ratings computed by third parties mainly by rating agencies. Basel Accord regulates the conditions for these types of rating systems.

In financial risk management, Basel agreements have very significant importance for financial institutions. Basel II is assumed to be most important agreements where Basel III is a modified version of Basel II in some failing points.

In 1988, central government institutions started to negotiate and agreed on some international standards and published a set of minimum requirements for capital to be kept especially in the banks in order to mitigate the credit risk in case of a possible crisis to be faced. This was the Basel I. By these requirements, banks are required to keep mandatory capital which is also known as regulatory capital or capital adequacy. Capital requirement is defined as the amount of capital that the financial institution has to hold to guarantee not to become insolvent.

Because the complexity of the sector increases, Basel I lost its sufficiency to regulate the sector and in 1999, Basel Committee on Banking Supervision released Basel II. The implementation just started in 2007. It became the backbone of international banking and still continues since Basel III only amends Basel II.

There are 3 pillars in Basel II which are Minimum Capital Requirement, Supervisory Review and Market Discipline. Credit risk is included in the first pillar which explains the details of the capital requirements by considering three major components of risk where two others are market risk and operational risk.

Basel II introduced 3 methods to assess the credit risk. They are Standardized Approach (SA), Foundation Internal Rating Based Approach (F-IRB) and Advanced Internal Rating Based Approach (A-IRB). These methods are listed in terms of their complexity. In all of methods, capital requirement is dependent on the Risk Weighted Asset (RWA). Capital Requirement is estimated by the regulator as 8% of RWA.

SA is used by institutions which are not expert enough to use other methods. In this method, the risk weights are given by the regulator according to several attributes. In the table below the risk weights are given (Table-3.2).

Table-3.2: Risk Weights

Credit Assessment	**AAA to AA-**	**A+ to A-**	**BBB+ to BBB-**	**BB+ to B-**	**Below B-**	**Unrated**
Risk Weight	0	0.2	0.5	1	1.5	1

According to the table, the capital requirement for the most risky institution is 12% which is 150% multiplied by 8%.

In F-IRB, RWA is computed after estimating default probability internally. Then using the formulas prepared by the regulator, RWA and capital requirement is computed. It means the only area of freedom is estimating default probabilities. The details and given formulas by the regulator are explained in Chapter 4.

In A-IRB, the institutions can compute other parameters such as LGD and EAD internally and freely. However it should not be forgotten that the regulator checks the models before its official use. After approval, the financial institution uses the models which are not imposed by the regulator to obtain RWA and capital requirement.

The capital requirement found is expected to decrease when more sophisticated approaches are used. So, A-IRB often allows financial institutions, especially banks, to decrease their capital requirements. Also F-IRB gives lower capital requirement than SA.

3.3. Study Background

The guarantee mechanism of the process can be illustrated in the Figure-3.4.

Figure-3.4: Guarantee Mechanism

Creditor gives loan to the Municipality at a rate which is higher than the rate of the loan given with a guarantee. In case the payment obligations of the Municipality are not fulfilled, guarantor fulfils the obligations. Then UoT, as guarantor, restructures the payment made to the Creditor as a new debt of the Municipality. Municipality starts to make related payments to UoT.

Thus, calculation of guarantee premium and determination of the capital requirement are crucial. To do so, the default probabilities need to be estimated. Default probabilities of the Municipality can be estimated from several different perspectives. In our study, we estimate these default probabilities by relating the various characteristics with the payment history of the Municipality. Logistic Regression and Artificial Neural Networks models are used and compared with respect to their error terms. In order to calculate the fair guarantee premium, a proxy rate which is a hypothetical rate of the loan Creditor gives to the Municipality without a guarantee needs to be known. If the credibility of the municipality is known by the creditor, the guarantee premium can be calculated without needing the default probability of the Municipality since the counterpart risk is included in the analyses of the Creditor and the interest rate offered includes the risk. However, the proxy rate cannot be calculated by the Creditors usually, especially for the municipalities since there is lack of information about their financial situations. Thus, by the help of estimated default probability, a proxy rate is calculated. Then, using the difference between the rate of the loan with guarantee and proxy rate, the guarantee premium is calculated. Credit Default Swaps or Interest Rate Difference can be utilized to calculate the fair guarantee premium in this respect.

In the last part of the study, we question the limits applied to guarantee premium in practice. Also, we apply stress testing to our models by changing main parameters and see how reliable our model is.

CHAPTER 4

PROPOSED METHODS

In this section, we will explain the methods used in this study to estimate the default probabilities and calculate the guarantee premium.

4.1. Methods for Estimating Default Probabilities

Before estimating default probabilities, we need to make a clear definition of default. In our study, default is defined for each year and the municipality is accepted as defaulted if one of the payment obligations in the related year is not met by the municipality. This definition makes it easy to relate the defaulted transactions of the municipalities with their input variables calculated yearly. Below, the models to estimate default probabilities are represented.

4.1.1. Logistic Regression (LR)

Logistic regression models are a type of Generalized Linear Models. In this model the distribution of the specified entity is assumed as Bernoulli. There is a link function called logit and unknown parameter is estimated by conducting iterative optimization method. We have a binary dependent variable (Y) in our model. Logistic regression will be used to discover the relation between the dependent variable and input variables (V). Outcomes of the response variable can be defined as; default event denoted by 1 with *P(Y=1 given v) = p(v)* and non-default event denoted by 0 with *P(Y=0 given v) = 1-p(v).* Then the model can be defined as:

$$0 \leq p(v) = \frac{e^{b_0+b_1V_1+\cdots+b_kV_k}}{1+e^{b_0+b_1V_1+\cdots+b_kV_k}} \leq 1$$

where $b_0, \ldots . b_k$ are the parameters of the model. In between the dependent variable and input variables there exists curvilinear relation. This is equal to:

$$odds(Y = 1) = \frac{\mathrm{P(Y = 1)}}{\mathrm{P(Y = 0)}} = \frac{\mathrm{p(v)}}{1 - \mathrm{p(v)}} = e^{b_0 + b_1 V_1 + \cdots + b_k V_k}$$

Since we used link function of logit, we can define model as a function of logit transformation:

$$\ln(odds) = \log\left[\frac{p(v)}{1 - p(v)}\right] = b_0 + b_1 V_1 + \cdots + b_k V_k$$

As can be interpreted from the model, the slope coefficient b_i represents change in the log odds values for an increase one unit in input variable v_i. In other terms, one unit increase in v_i yields odds values multiplied by e^{b_i}.

Odds values are important for Logistic Regression Model. We can explain odds values for a chosen variable v_{24}= Is the related year election year? Suppose that the contingency table for variable v_{24} is arranged hypothetically as below (We cannot give the actual numbers due to the privacy concerns):

Table-4.1: Contingency Table

	v_{24}		
Dependent Variable (Y)	0	1	Total
0	57	13	70
1	13	7	20
Total	70	20	90

By using the table above, we can study the conditional distribution. There are 90 observations classified as default and non-default.

For $v_{24} = 0$, the proportion of defaulted transaction is 13/70 = 0.19 (with two significant numbers used) and for non-defaulted transaction is 57/70 = 0.81.

For $v_{24} = 1$, the proportion of defaulted transaction is 7/20 = 0.35 and for non-defaulted transaction is 13/20 = 0.65.

Then odds values can be computed as follows:

Odds (Y=1 given $v_{24} = 0$) = 13/57 = 0.19/(1-0.19) = 0.23, and

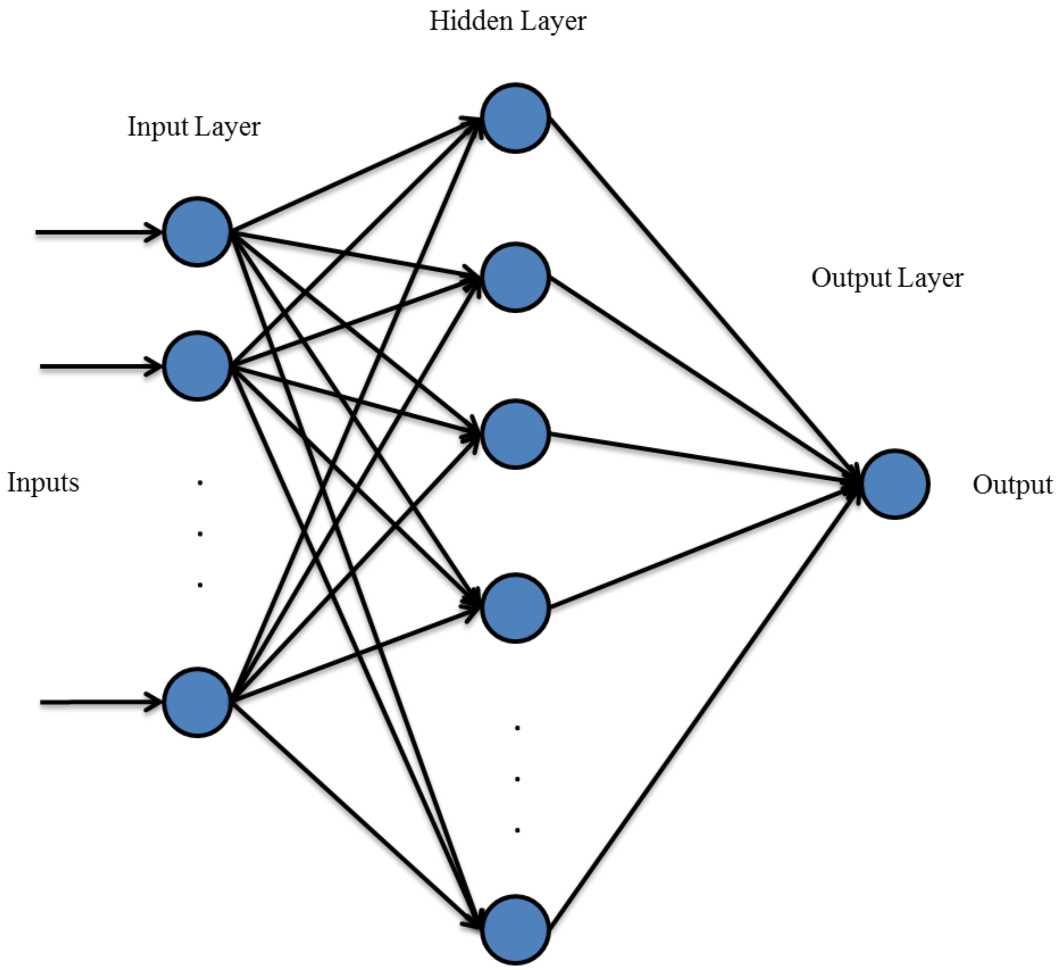
Odds (Y=1 given $v_{24} = 1$) = 7/13 = 0.35/(1-0.35) = 0.54.

The ratio of odds values (= θ (odds ratio) = 0.54 /0.23) is equal to 2.35 which means the probability of default in an election year is 2.35 times larger than the probability of default in an non-election year. When this ratio is higher towards infinity or lower towards 0, the input variable is more explanatory (C. Lu et al, 2001). In the following sections, we will explain variable selection methods used in the study.

4.1.2. Artificial Neural Networks (ANNs)

ANNs are the combination of interconnected processing units inspired by the biological neural nets transmitting signals via neurons and synapses. The method comprises the ability of capturing complex relationships between input and output information within the network structure. One of the most important advantages of ANNs is their capability of providing information about nonlinear and hidden patterns in the data. Although the network implementation is usually considered as a black box, ANNs' power simply comes from their execution; they implement linear discriminants while inputs have been mapped nonlinearly in space. The key power of neural networks is dependent on implementation of fairly simple algorithms where nonlinearity can be learned from the training data.

There are different types of neural networks and feed-forward neural network (FFNN) is used in this study. FFNN consists of neurons in layers which are connected in a form that the output from one layer is distributed to the inputs of the succeeding layer. The layers between the inputs and output layer are called as hidden layers. The input values are transmitted to the hidden layer with assigned weights and bias values to them. During this process, the activation function (sigmoid transformation function) is used. Same process continues and final values with related weights and bias values are summed for the output layer. The last value which is output is obtained with an error term. Learning can be provided by updating the weights and bias values with respect to this deviation (error) term. The back-propagation algorithm used here is the core learning algorithm for FFNN. In the figure below, the model is presented.



Figure–4.1: Feed-Forward Neural Network Structure

In the study, sigmoid transformation functions are used among the other functions such as log-sigmoid, hyperbolic tangent sigmoid and linear. Sigmoid transfer function is described as:

$$f(net) = \frac{1}{1+e^{-net}},$$

where net is the input of the preceding layer and f(net) is the output of the succeeding layer.

It should be kept in mind that for a single layer neural network with linear transfer function applied in the output layer, the system can be interpreted as a linear regression model. Similarly, a network with logistic transfer functions in the output layer is equivalent to logistic regression model. Thus, the results coming from the models and default probabilities are congruent.

In the network, the nodes are interconnected with moving weights and bias values. The transformation function mentioned above is used in hidden layers and output layer. The weighted sum of the inputs is described as:

$$(net_j) = \sum_{i=1}^{p} x_i w_{ji} + b_j \ ,$$

where x_i is the i-th input variable in the preceding layer with w_{ji} representing the weights from the preceding layer to the hidden layer and b_{j0} representing the bias values assigned. The transformation function is applied to net_j to find the output. The model representation with three layers and g, j, k nodes in the layers can be seen below:

$$(\hat{y}_t) = f(\sum_{j=1}^{n_h} w_{gj}\, f\,(\sum_{i=1}^{p} x_i w_{ji} + b_j) b_t)$$

where n_h is the number of the hidden nodes in the output layer and p is the number of nodes in the input layer. w_{gj} represents the weights from hidden layers to the output layer and b_j *and* b_t represent bias values.

In neural network models, training is a crucial part since the updated weights and bias values are needed to reach the best predictive result. As we mentioned above, we used back-propagation algorithm for network training. After producing output result, the weight and bias values are updated in the direction of error term and a learning rate used.

Each network initializes itself with random weight and bias values. It means each network is different with different weight and bias values. The weight and bias values are updated until pre-defined performance criterion for convergence is obtained. One of the criteria we used in the study is 'Maximum number of epochs'. Epoch is defined as updating weight and bias values by using all the observations in the data set. Another criterion we used is the 'performance goal', which provides termination if the performance goal is obtained.

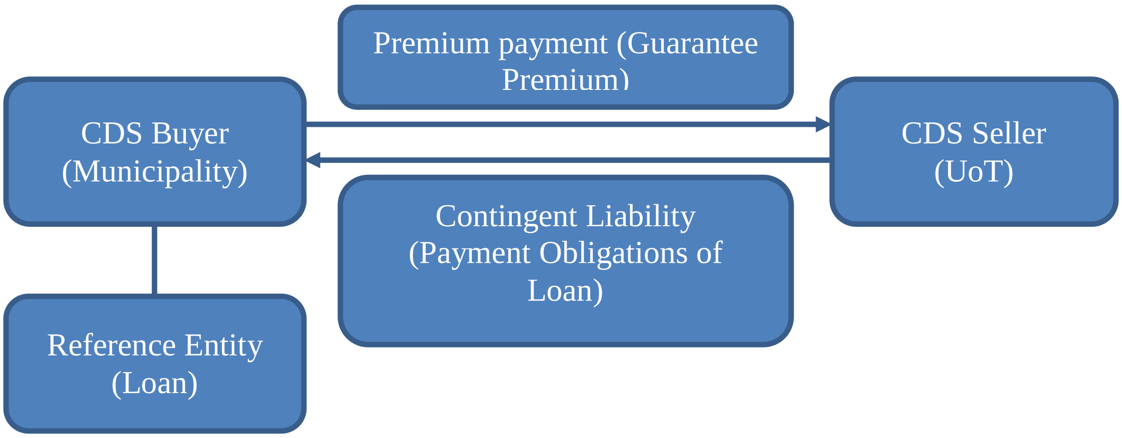
4.2. Methods for Calculating Guarantee Premium

There are several tools that could be used to compute fair guarantee premium, such as credit default swaps, interest rate difference and expected loss pricing. Also, option pricing models can be employed to compute the guarantee premium. We briefly mention the types of transactions used in this study.

4.2.1. Credit Default Swaps (CDS)

Financial derivatives are increasingly used to determine the value of a loan guarantee. Derivatives are assets whose payoffs are dependent on future prices of some other assets. They can also be called as contingent claims. CDS is one of the most popular forms of derivatives.

When a CDS (which is a kind of insurance to prevent the credit risk) is applied to a loan, CDS seller becomes the guarantor of the loan. In case of borrower (which is generally also the buyer of CDS) default, seller pays the obligations of the loan to the Creditor. The principles of CDS and the guarantee mechanism on a loan are indistinguishable. Thus, CDS premiums can be set as benchmark for a fair guarantee premium. The operations in CDS are summarized in the figure below:



Figure–4.2: CDS Operations

The buyer makes a lump-sum payment to the seller and payment obligations of the loan is secured. In case of default, seller continues to make payments until the maturity of the loan. Default definition has three broad categories in real world. These are bankruptcy, failure to pay and restructuring. In our case, Municipality is the CDS Buyer, thus bankruptcy is not an option. Restructuring means changing the payment schedule on the loan. These types of changes are very few and excluded from this study.

The CDS markets have high trading volume. They are highly liquid. On the other hand, CDS transactions are complex and challenging to describe that instrument to the related stakeholders. The usual valuation method for the study is to find the CDS premium within the market. Since we do not know where the municipalities fit on the ratings scale in the financial markets, we choose the primary valuation method as valuing the swap directly.

In valuing CDS, no-arbitrage principle is applied like pricing any other derivatives. Because derivative assets derive their value from the underlying asset, the derivative can be replicated by trading the underlying risky asset and a risk-free asset. If a portfolio that consists of the derivative asset and the replicating portfolio can be set up at zero cost today, and has a positive probability of gain in the future, we conclude that an arbitrage exists. If the derivative is cheaper, then the trading strategy will be to take a long position (buying) in the derivative asset and a short position (selling) in the replicating portfolio. Conversely, if the derivative is more expensive, then the trading strategy would be to take a short position in the derivative asset and a long position in the replicating portfolio. The goal in valuation of derivatives is pricing derivatives to avoid the arbitrage opportunities.

Our portfolio mentioned above consists of risk-free loan and risky loan. The value of the risky loan is the cash flow from the Municipality loan discounted at the *proxy rate* which is the interest rate to be applied by the Creditor to the municipalities without any guarantee. The calculation of the proxy rate is explained later.

At loan initiation, UoT makes a one-time payment into the hedge which is the guarantee premium received from the Municipality. The hedge uses this cash plus the cash from a short position in the Municipality loan to fund a long position in the risk-free loan.

Municipality can either make the scheduled payment or defaults at each payment date just before payment is made. If Municipality does not default, then the value of the short position in the Municipality loan is the loan principal balance plus accrued interest, and the value of the short position in the CDS is zero. If the Municipality default, then the value of the short position in the Municipality loan is the expected payment to Creditor in satisfaction of the loan guarantee. The remaining cash balance which is the CDS premium of that period in the portfolio is zero if Municipality defaults, and is equal to the amount of cash needed to set up the hedge in the next period if Municipality does not default.

The mentioned short and long positions are two legs used to price the CDS which are fixed leg and contingent leg. They create a portfolio with separate weights to prevent the arbitrage. It means the expected payments need to be equal to expected losses in the portfolio with respect to given default probability, recovery rate and interest rate in order to avoid free lunch in the market.

The fixed leg is calculated with survival probabilities considering periodical premium payments but in our model, municipality makes one-time payment at the loan initiation which makes the calculations easier.

In the contingent leg, there are two components in asset and liability sides. First one is the risk-free loan in the asset side. The second one is the municipality loan which is the contingent liability for UoT. It means the payoffs of selling CDS can be obtained by constructing a portfolio which has long position in risky loan and short position in risk-free loan. The equation can be seen below:

Risk-free loan = Risky loan + CDS Premium

CDS Premium = ω_1 *x Risk-free loan -* ω_2 *x Risky loan*

In every period, the weights (ω_1 and ω_2) of the positions in the portfolio are calculated and CDS Premium at time 0 is calculated.

First thing we need to set is the loan amount and amortization schedules with respect to the related discount rates. Here we assumed that UoT has borrowing with the risk-free rate (r) of 6%. Sometimes, UoT cannot borrow with risk-free interest rate and this can change the CDS premium. We examine the effect of the difference between the risk-free interest rate and Municipality borrowing rate which is the Interest Rate Spread (IRS).

Since we do not know the interest rate to be applied by the Creditor to the municipalities, we need to calculate a proxy rate (r_p) by using default probabilities estimated by ANN model, loss given default and risk-free interest rate. Creditor's lending rate without the loan guarantee is shown in formula below (Schurman, 2010):

$$r_p = \frac{(1 + r) - (1 - LGD)\ x\ PD}{(1 - PD)}$$

After constructing loan amortization schedules, the weights of the assets at the maturity are set to 1.

The portfolio asset weights need to be assigned in such a way that any change in the value of the derivative asset is offset by the same change in the value of the underlying asset, making the portfolio risk-free which is representing no opportunities for arbitrage. From this portfolio, a PDE (functions that describe how portfolio value changes) and a solution to the PDE need to be derived. The PDE and the solution of the hedge portfolio are:

$$PDE: r\frac{\Delta C_t}{\Delta L_t}L_t + \frac{\Delta C_t}{\Delta t} - rC_t = 0$$

$$Solution: C_t = \omega_{1t}B_t(1+r) - \omega_{2t}L_t$$

where C_t is the value of the CDS at time *t*,

L_t is the value of the Municipality loan at time *t*,

B_t is the value of the risk-free loan at time *t*,

r is the risk-free interest rate and

ω_{1t} and ω_{2t} are the weights assigned to B_t and L_t respectively at time *t*.

The weights are found by using the solution of PDE above. According to the solution of PDE, a CDS can be replicated using a risk-free loan and the underlying risky loan as expected. In other words, the value of CDS at time *t* (C_t), can be calculated with the weighted average of risk-free loan (B_t) and municipality loan (L_t) where the weights are ω_{1t} and ω_{2t}, respectively. At the initial point where the loan originates and after each payment date (except for the final payment), a portfolio needs to be created. At each payment date (before the payment is received or the loan defaults), the hedge is unraveled. The weights of the equation above can be calculated by creating two equations with two unknowns since we know the value of the CDS at each payment date given default or no default which are the boundary conditions. The asset weights are defined as (Schurman, 2010):

$$\omega_{2t} = \frac{C_{dt} - C_{nt}}{L_{nt} - L_{dt}}; \quad \omega_{1t} = \frac{\omega_{2t}L_{dt} + C_{dt}}{B_t(1+r)},$$

where C_{nt} is the value of the CDS at time *t* if Municipality is not in default (its initial value is 0 at the maturity),

C_{dt} is the value of the CDS at time *t* if Municipality default,

L_{nt} is the value of the Municipality loan at time *t* if Municipality is not in default and

L_{dt} is the value of the Municipality loan at time *t* if Municipality default.

All the parameters used in the calculation of the weights are derived from the amortization schedules of the risk-free and risky loans.

Since this is a loan guarantee premium calculation containing several periods, how much cash to be kept at the end of each period must be known. Thus, we work backwards from last payment to the initial payment. Using the updated weights, we compute the CDS price at each payment date at time t. After C_t is found it becomes new C_{nt} and the process repeats for the preceding period. C_t value at the loan initiation is the guarantee premium to be applied. The process can be explained with an example:

Suppose that a municipality has to make payments of $38.8 at the end of each year with a maturity of 3 years and the Creditor applies 8% interest since the loan is backed with UoT guarantee (IRS is assumed as 2% since the risk-free interest rate is assumed as *r=6%*). The loan amortization schedule with given conditions is represented in Table-4.2 below:

Table-4.2: Loan Amortization Schedule

t	Loan Balance	Payment	Principal	Interest
0	100.00	-	-	-
1	69.20	38.80	30.80	8.00
2	35.93	38.80	33.27	5.54
3	0.00	38.80	35.93	2.87

The contingent liabilities for each period if the municipality defaults can be shown in Table-4.3 below:

Table-4.3: UoT's Estimated Contingent Liabilities

t	Principal	Interest	UoT Contingent Liability (C_{dt})
1	100.00	8.00	108.00
2	69.20	5.54	74.73
3	35.93	2.87	38.80

It is assumed that the underlying project is not depreciable and has no auction value for it. That is why, C_{dt} is the sum of principal and interest. If there was auction values, it would be subtracted from the sum.

We have assumed that the risk-free interest rate is 6%. Since, there are risk-free and risky loan in the portfolio; we need the loan amortization schedule for risk-free and risky loans (Table-4.4 and Table-4.5).

Table-4.4: Loan Amortization Schedule of Risk-free Loan (*r=6%*)

t	Loan Balance($B_{(t+1)}$)	Payment	Principal	Interest
0	103.72	-	-	-
1	71.14	38.80	32.58	6.22
2	36.61	38.80	34.53	4.27
3	0.00	38.80	36.61	2.20

Table-4.5: Loan Amortization Schedule of Risky Loan (r_p=*10%*)

t	Loan Balance ($L_{(t+1)}$)	Payment (L_{nt}-$L_{(t+1)}$)	Principal	Interest
0	95.76	-	-	-
1	66.95	38.80	28.81	9.99
2	35.14	38.80	31.82	6.99
3	0.00	38.80	35.14	3.67

Then using the calculation method explained in above, we find the weights and CDS premium (Table-4.6).

For *t=3*;

$$\omega_{23} = \frac{C_{d3} - C_{n3}}{L_{n3} - L_{d3}} = \frac{38.8 - 0}{38.8 - 0} = 1\ ; \quad \omega_{13} = \frac{\omega_{23} L_{d3} + C_{d3}}{B_3(1+r)} = \frac{1x0 + 38.8}{36.61x(1.06)} = 1\ ,$$

$$C_3 = \omega_{13} x B_3 - \omega_{23} L_3 = 1x36.61 - 1x35.14 = 1.47$$

$$C_{n2} = C_3 = 1.47$$

For *t=2*;

$$\omega_{22} = \frac{C_{d2} - C_{n2}}{L_{n2} - L_{d2}} = \frac{74.73 - 1.47}{73.94 - 0} = 0.99\ ; \quad \omega_{12} = \frac{\omega_{22} L_{d2} + C_{d2}}{B_2(1+r)} = \frac{0.99x0 + 74.73}{71.14x(1.06)} = 0.99,$$

$$C_2 = \omega_{12} x B_2 - \omega_{22} L_2 = 0.99x71.14 - 0.99x66.95 = 4.16$$

$$C_{n1} = C_2 = 4.16$$

For *t=1*;

$$\omega_{21} = \frac{C_{d1} - C_{n1}}{L_{n1} - L_{d1}} = \frac{108 - 4.16}{105.76 - 0} = 0.98\ ; \quad \omega_{11} = \frac{\omega_{21} L_{d1} + C_{d1}}{B_1(1+r)} = \frac{0.98x0 + 108}{103.72x(1.06)} = 0.98\ ,$$

$$C_1 = \omega_{11} x B_1 - \omega_{21} L_1 = 0.98x103.72 - 0.89x95.76 = 7.86$$

Table-4.6: Valuing the Credit Default Swap

Description	Symbol	t=3	t=2	t=1
CDS payment - No default	C_{nt} ($C_{(t+1)}$)	0.00	1.47	4.16
CDS payment - Default	C_{dt}	38.80	74.73	108.00
Municipal loan value - No default	L_{nt}	38.80	73.94	105.76
Municipal loan value - Default	L_{dt}	0.00	0.00	0.00
Municipal loan value - Begin year	L_t	35.14	66.95	95.76
Risk-free loan value - Begin year	B_t	36.61	71.14	103.72
Risk-free loan equation weight	w_{1t}	1.00	0.99	0.98
Municipal loan equation weight	w_{2t}	1.00	0.99	0.98
CDS value - Begin year	C_t	1.47	4.16	7.86

L_{dt} is zero for each period since it is assumed that the underlying project is has no auction value. In other words, if municipality is in default at time *t*, municipal loan value is zero at that time.

As seen from the table above, the premium value is $7.86 which is 7.86% of the loan balance at time 0. If we assume that the actual loss is $6.5 due to the defaults of the municipality, Mean Percentage Error for CDS premium is found as;

$$MPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{Guarantee\ Premium_i - Actual\ Loss_i}{Actual\ Loss_i}$$

$$= \frac{100\%\ x\ (7.86 - 6.5)}{6.5} = 20.87\%$$

where $Guarantee\ Premium_i$ is the guarantee premium calculated for Municipality *i* and $Actual\ Loss_i$ is the actual loss compensated for Municipality *i*.

The premium values and the error terms for other methods are shown in the Table-4.7 below:

Table-4.7: Hypothetical Guarantee Premium and Error Term Values

	CDS	IRD	EL
Guarantee Premium	7.86	4.24	3.73
MPE	20.87%	-34.84%	-42.55%

In summary, **to price the CDS** when the hedge is set up, we need the **portfolio asset weights and the market values of the risky (L_t) and risk-free loans (B_t) at that time**.

The assumptions of the model and computational study are described in Chapter 5.

4.2.2. Interest Rate Difference (IRD)

In essence, the base here is focusing on the difference between applied interest rates of the risky loan and risk-free loan. In order to apply this method, municipality's benefit received by UoT guarantee needs to be quantified.

Thus, the interest rate the municipality would have paid if it has borrowed alone is determined. Then, the interest rate offered when there is a guarantor is determined. Lastly, the difference between the present values of the loan payments at the risk-free and risky (proxy) rates is computed. Since we assumed this difference caused only from the credit risk, it can be shared between the guarantor and the municipality. The division of the difference is a subject of another study but we assume that UoT takes all of the difference which is the maximum guarantee fee although it is unlikely in practice.

Because the portfolio constructed in CDS pricing is taking a short position in the risky loan and a long position in the risk-free loan, the value of the CDS can be approximated by this approach.

4.2.3. Expected Loss (EL) Pricing

EL pricing can be also conducted to calculate a benchmark for the guarantee premium. In financial terms, the guarantee premium is equal to the arm-length premium for insuring the underlying loan. The pricing for financial guarantee premium can be computed using default probabilities multiplied by the present worth of the future payment obligations of the entity. The related formula can be seen below:

$$EL = \sum_{k=1}^{n} \frac{CF_k}{(1+r)^k} \ x \ DPx \ LGD$$

where *k* denotes the periods while there are *n* periods.

4.2.4 Basel Accord Capital Requirements

The capital requirements set by Basel Accord can be interpreted as another benchmark. As we explain in Chapter 3, the capital requirement for an institution lending money to a counterparty with the lowest rating is 12% if the Standardized Approach (SA) is applied.

As another approach of F-IRB, RWA is computed after estimating default probability internally. Then using the formulas prepared by the regulator, RWA and capital requirement is computed.

An important parameter for finding capital requirement under IRB approach is the worst case default rate (WCDR) which is defined as the 99.9% quantile of the default rate distribution which is assumed as standard Gaussian distribution. The formula for WCDR is (Basel II, 1998):

$$WCDR = \phi(\frac{\phi^{-1}(PD) + \sqrt{\rho}\phi^{-1}(0.999)}{\sqrt{1-\rho}})$$

where ρ is the pairwise correlation factor for the default. It is given for corporate, sovereign and bank exposure as:

$$\rho_i = 0.12 \ (1 + e^{-50 \ x \ PD})$$

After calculating *WCDR*, the equation below is used for computation of capital requirement:

$$Capital \ Requirement = EAD \ x \ LGD \ x \ (WCDR - PD) \ x \ MA$$

where MA is maturity adjustment which is calculated with the equation below:

$$MA = \frac{1 + (M - 2.5)\ x\ b}{1 - 1.5\ x\ b}$$

where M is the average maturity of the underlying asset and b is a correction factor which is computed as:

$$(0.11852 - 0.05478\ x\ \ln(PD))^2$$

So we substitute the default probabilities of the municipalities into the equations above and the capital requirement for each loan is computed. Then capital requirements for each loan are summed in the risk account.

In F-IRB, the capital requirement can be expected lower than the capital requirement calculated in SA since a more realistic approximation can be achieved by calculated a more accurate PD. After calculations, we found that this is true for our case also. As we will see in Chapter 5, even 12% of capital requirement designated in SA gives high error terms. That is why, it can be concluded that using F-IRB cannot outperform other tools used to calculate guarantee premium.

CHAPTER 5

COMPUTATIONAL STUDY

Firstly the dataset used in the study is described in Section 5.1. After that, pre-processing of data is explained in Section 5.2. Lastly, in Section 5.3 and 5.4., the results and validation for default probability predictions and guarantee premium calculation are given.

5.1. Data Description

As we addressed earlier, the municipalities might be able to borrow foreign financing with UoT Guarantee or with Onlending. The repayment installments mean contingent liability for Treasury without depending on whether the credit is provided with Treasury Guarantee or it is an Onlending. The received payment history is our first dataset. If the payment is received after its projection date, Treasury pays the obligation instead. The payment history of 18 municipalities between the years of 1997 and 2009 is collected.

Then, the ratios in four different categories which are economic ratios, financial ratios, debt-related ratios and administrative ratios are linked to the payment history of the municipalities.

Payment history of the municipalities, financial and debt-related ratios are provided by UoT within the frame of a Confidentiality Agreement. Economic ratios are provided by TURKSTAT. There are 25 ratios and variables where two of them are binary. The dependent variable is also binary with the categories 0 indicating non-defaulted and 1 indicating defaulted municipalities. If a municipality does not make at least one payment before or on due date in a specific year, we counted the municipality as defaulted in that year. The data set is composed of 90 transactions showing yearly repayment history of the credits. Input ratios and variables can be shown in the Table-5.1.

Table-5.1: Input Variables

Financial ratios	Debt-related ratios
$v_1 = \frac{\text{Self Revenues}}{\text{Total Revenues}}$	$v_{13} = \frac{\text{Debt Service}}{\text{Total Revenues}}$
$v_2 = \frac{\text{Shares from Central Budget}}{\text{Total Revenues}}$	$v_{14} = \frac{\text{New Borrowing}}{\text{Current Expenditures}}$
$v_3 = \frac{\text{Interest Expenditures}}{\text{Total Revenues}}$	$v_{15} = \frac{\text{New Foreign Borrowing}}{\text{Capital Expenditures}}$
$v_4 = \frac{\text{Financial Surplus (Deficit)}}{\text{Total Revenues}}$	$v_{16} = \frac{\text{New Borrowing}}{\text{Debt Service}}$
$v_5 = \frac{\text{Operational Balance}}{\text{Investments}}$	$v_{17} = \frac{\text{New Borrowing}}{\text{Capital Expenditures}}$
$v_6 = \frac{\text{Tax Revenues}}{\text{Total Revenues}}$	$v_{18} = \frac{\text{Total Debt to Treasury}}{\text{Total Revenues}}$
$v_7 = \frac{\text{Operational Expenditures}}{\text{Total Expenditures}}$	$v_{19} = \text{Increase rate in Debt to Treasury}$
$v_8 = \frac{\text{Capital Revenues}}{\text{Total Revenues}}$	$v_{20} = \text{Increase rate in Debt Service}$
$v_9 = \frac{\text{Total Revenues}}{\text{Total Expenditures}}$	v_{21} = Lag Variable: The average of default probabilities of the past transaction of the related municipality.
$v_{10} = \frac{\text{Personnel Expenditures}}{\text{Total Expenditures}}$	
$v_{11} = \text{Increase rate in Self} - \text{Revenues}$	
$v_{12} = \text{Increase rate in } \frac{\text{Total Revenues}}{\text{Total Expenditures}}$	

Economic ratios	Administrative ratios
$v_{22} = \text{Population}$	v_{24} = Is the related year election year ? (Binary)
$v_{23} = \frac{\text{Working Population}}{\text{Total Population}}$	v_{25} = Is the party of Mayor Government Party ? (Binary)

5.2 Data Diagnostic

The role of data diagnostic is to understand the past. In order to interpret the past transactions better, data can be evaluated by descriptive statistical techniques.

Mean of the data set is more meaningful when it is interpreted together with the standard deviation of the data set which expresses the distance from the mean. They are connected since higher the variance, the less explanatory the mean is. Beside the mean and standard deviation, the minimum and the maximum values for the variables are also investigated. Descriptive statistic for the independent variables is summarized in Table-5.2. The difference between the maximum and the minimum value and the variability of variables v_{16} (New Borrowing/Debt Service) and v_{22} (Population) are very high. Thus, it can be concluded that the means of these variables are less representative for the data set.

Table-5.2: Descriptive Statistics for Variables

Variable	Mean	Std. Dev.	Min	Max
v_1	0.4450	0.1878	0.1543	0.9077
v_2	0.5355	0,1823	0.0921	0.8456
v_3	0.0503	0.0775	0.0000	0.5926
v_4	-0.1681	0.2769	-1.3069	0.3673
v_5	0.5427	1.0318	-3.9536	5.9868
v_6	0.0904	0.0605	0.0039	0.2420
v_7	0.6943	0.1679	0.3487	1.2331
v_8	0.0783	0.0875	0.0000	0.4254
v_9	0.8976	0.1910	0.4335	1.5804
v_{10}	0.2265	0.1248	0.0004	0.5550
v_{11}	0.4580	1.1272	-0.9066	7.1806
v_{12}	-0.0034	0.3179	-0.5917	1.7666
v_{13}	0.1783	0.2097	0.0000	0.9875
v_{14}	0.9993	1.6932	-0.7254	9.6765
v_{15}	0.1969	0.5730	-0.0058	4.7824
v_{16}	15.8179	68.6277	-11.2804	624.8880
v_{17}	1.9296	3.0189	-0.7222	13.0368
v_{18}	1.8093	3.4883	0.0019	25.2398
v_{19}	0.7123	2.2171	-0.9881	13.1705
v_{20}	1.1766	3.2434	-1.0000	19.6059
v_{21}	0.6055	0.3999	0.0000	1.0000
v_{22}	1,727,634.2857	1,150,980.0585	291,528	4,650,802
v_{23}	0.6531	0.0530	0.5242	0.7219

5.2.1. Pre-Processing

Generally it is needed to have 10 observations for each parameter in the data set to be able to see the justifiable effects of the variables (Harrell, 2001). There exist lots of methods for dimension reduction, such as Factor Analysis and Principal Component Analysis (PCA). We applied these methods without looking at the response function to provide confident results. Using the significant variables again according to the result of the models is not a good idea since the whole picture cannot be considered in each iteration.

Thus, we firstly calculate the pairwise correlations of the variables. According to the results of the correlation matrix seen in the Appendix B, we remove five highly correlated variables which are $v_2, v_4, v_{12}, v_{14}, v_{19}$ from the data set.

If the input variables are on different scales, they should be transformed to the same scale to increase the efficiency of the results. In this study, the numerical ratios were all transformed to 0-1 scale with min-max scaling method after removing five correlated variables. By applying normalization to the data set, we prevent the network to perform poorly. Thus, reliable convergence of weight and bias values is produced by having input variables on the same scale.

Then, we applied PCA to numerical variables in order to reduce dimensionality further by removing variables adding minimum variability with holding total variability at the level of 0.95 after transformation of the variables. Ultimately, the 14 variables (2 of them as binary) are left as variables in the data set.

5.3. Numerical Results

5.3.1. Calculating Default Probabilities

5.3.1.1. Logistic Regression Results

Logistic Regression models do not require many assumptions as needed by the Linear Regression. Linear relationship between the dependent and independent variables is not sought since it can be handled by applying the log transformation to the predicted odds values. Also the independent variables and error terms do not have to be normally distributed. Lastly, the metric form of independent variables is not needed.

Even so, there are assumptions we need to make. Logistic Regression assumes that outcome of 0 or 1 is the probability of an event to occur or not. Thus, the dependent variable needed to be coded properly. Since the model needs to have little or no multicollinearity, the independent variables need to be assumed as independent. Factor analysis and PCA can be applied before the regression model is constructed. Another assumption of the model is that independent variables have linear relation with log odds.

Logistic regression gives an equation with the weights assigned to the input variables like any other regression model. Applying logistic regression does not require the assumptions of normality and linear relations between the variables. Since the data division is made randomly in ANN, we have divided data random in applying logistic regression also. Two models with and without applying PCA is constructed by dividing data into training and validation set with the percentages of 80% and 20% respectively. After PCA applied, binary variables are included in the data set without any modification on them.

The equation does not produce values of 0 and 1; instead it provides log odds which are computed to estimate the default probabilities. The coefficients of the input variables are called logits but the change in the logits does not directly change the dependent variable since the transformation needs to be applied.

Since data division is random, there is no certain regression equation of our model but the most likely variables with high positive coefficients in the replications are:

- $v_7 =$ Operational Expenditures/Total Expenditures,
- v_8= Capital Revenues/Total Revenues

and where high negative coefficient is

- v_{24}= Is the related year election year?

After transforming the dependent variable, maximum likelihood estimation is applied and default probabilities are estimated. After PCA is applied, p-values of all the variables in the replications is found less than 0.05. Also, the average of chi-square statistics is found as 212.25. Chi-square statistics is calculated and seen for the replications that the model and variables are significant with 95% confidence level. Although it is not suggested to use pseudo R-square for LR, the average of 10 replications is calculated as 81.13%.

5.3.1.2. Artificial Neural Network Results

Many of the mathematical models assume the data has a distribution pattern. ANN does not require such assumptions on distribution pattern problem space.

A desirable network topology for the network is having a relatively small number of hidden layers and nodes and high predictive power. The final form of the network can be built by evaluating the validation error or number of iteration set.

In Matlab, we have constructed the code to find the best topology by dividing data into training, validation and test set with the percentages of 80%, 10% and 10% respectively. Two models with and without applying PCA is constructed. After PCA is applied, binary variables are included in the data set without any modification on them. We have set two criteria where one of them is minimizing validation error and second one is the number of iterations which is set to 100. We have tested the topologies with one hidden layer in which there are nodes numbered from 3 to 124 with 4 replications in the arrays of 11 due to computational concerns. Then fine tuning is done using nodes numbered from 8 to 16 in the arrays of 2. The error results of the topologies are given in the Appendix C. Training parameters of the model is given in the table below:

Table-5.3: Training Parameters

Maximum Number of Epoch	100
Learning Rate	0.01
Performance Goal	100
Maximum Validation Failures	5
Maximum Time to Train in Seconds	inf
Minimum Performance Gradient	1.00E-06

The final form of the network with minimum validation error has ten nodes in one hidden layer. In the network, scaled conjugate gradient algorithm is used as training algorithm with tangent sigmoid (tansig) transfer function. By this topology, training parameters and settings mentioned in section 4, default probabilities are estimated.

5.3.1.3. Validation Results for PD Estimating Models

The models presented in the previous section have different dynamics and significant variables. Thus, we tested prediction powers of the models to find the best model estimating default probabilities.

For the prediction power, Mean Absolute Errors (MAE) and Mean Squared Error (MSE) were estimated and compared for 10 replications. The performance of the models can be seen in Appendix D. Since we cannot give the actual numbers due to the privacy concerns we can explain the error terms with a hypothetical example. If we assume that the estimated default probabilities of two municipalities are 5% and 10% respectively and the municipalities are not in default at that period,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|PD_i - Actual_i| = \frac{(|0.05-0|)+(|0.10-0|)}{2} = 7.5\% \; and$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(PD_i - Actual_i)^2 = \frac{(0.05-0)^2+(0.10-0)^2}{2} = 0.625\%$$

where PD_i is the probability of default of Municipality i and $Actual_i$ is the dependent variable denotes whether the Municipality *i* is in default or not.

In terms of actual error terms, ANN has the minimum errors after applying PCA on the data as seen from Table-5.4 below:

Table-5.4: Errors of Models

	LR		ANN	
	MAE	MSE	MAE	MSE
After Factor Analysis	1.41%	1.40%	1.12%	0.84%
After also PCA	1.25%	1.24%	**1.10%**	**0.75%**

In summary, our empirical results show that ANN outperforms Logistic Regression in terms of predictive power for the default probabilities.

Since our data set is limited, we have a concern for validation and test sample for the models. In order to test how accurately our models perform for an independent data set, we applied 10-fold cross validation. By using cross validation, the data is partitioned into 10 subsets. For LR, a single subset is kept for validation while the remaining 9 sets are kept for training for each run. For ANN, two subsets are kept for validation and testing while the remaining ones for training. The average of 10 runs is computed to have a single result. By doing this, we used all the observation for both in the training set and the validation set (and test set in ANN). The process for the models is briefly explained in the Figure-5.1 and Figure-5.2 below:

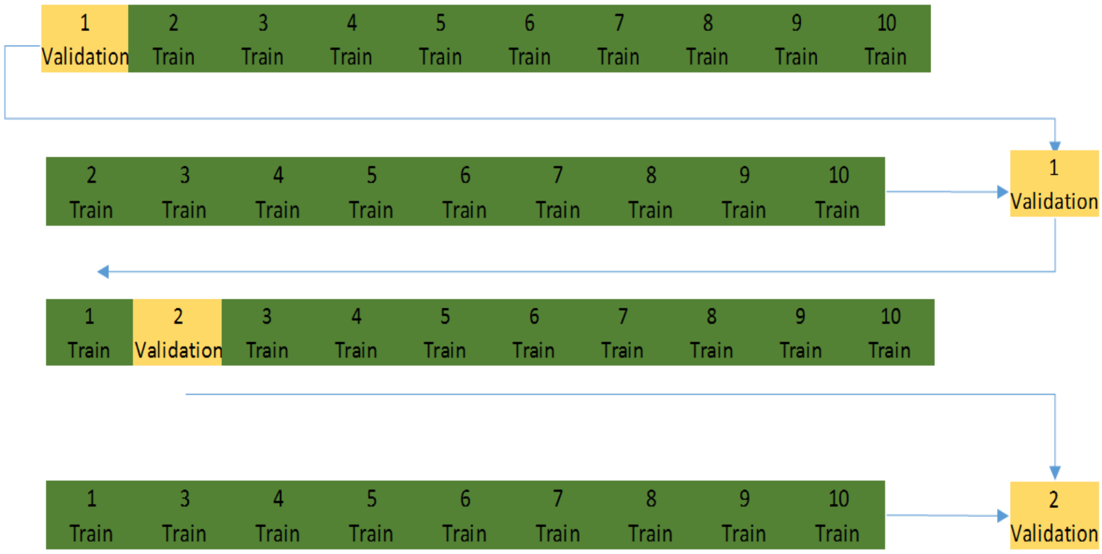


Figure-5.1: 10-fold Cross Validation Application for LR

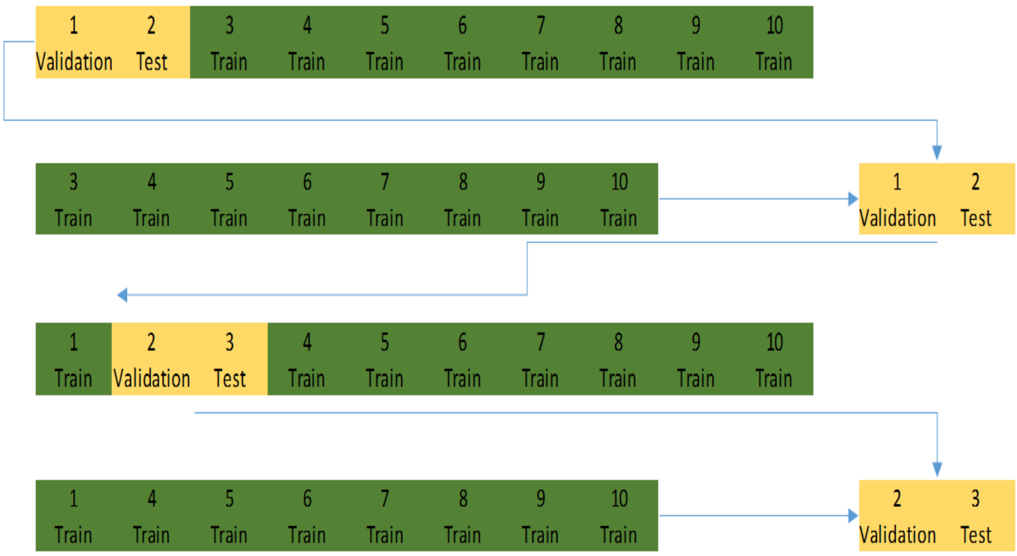


Figure-5.2: 10-fold Cross Validation Application for ANN

This process is repeated 10 times and the average of the overall error terms is reported in Table-5.5 below.

Table-5.5: 10-fold Cross Validation Results of Models

	LR		ANN	
Repetition	MAE	MSE	MAE	MSE
1	1.85%	1.85%	1.48%	1.32%
2	1.23%	1.22%	0.88%	0.73%
3	1.76%	1.76%	1.66%	0.88%
4	2.04%	2.04%	1.13%	1.02%
5	1.97%	1.96%	1.10%	0.90%
6	1.67%	1.65%	1.39%	1.12%
7	1.70%	1.70%	1.62%	1.58%
8	0.88%	0.88%	2.25%	1.61%
9	1.70%	1.70%	1.54%	1.24%
10	1.65%	1.65%	0.77%	0.62%
Average	1.65%	1.64%	1.38%	1.10%

Although the error terms seem to be little higher after applying cross-validation, ANN model still outperforms LR.

In order to measure the explanatory power of the models, Receiver Operating Characteristics (ROC) curves are examined and Area Under Curve (AUC) values are compared. The curve of the true positive rate against false positive rate is defined as ROC curve. The steeper the curve, the better the explanatory power of the model is. ROC curves for the last replication of the models are given in the figures below:

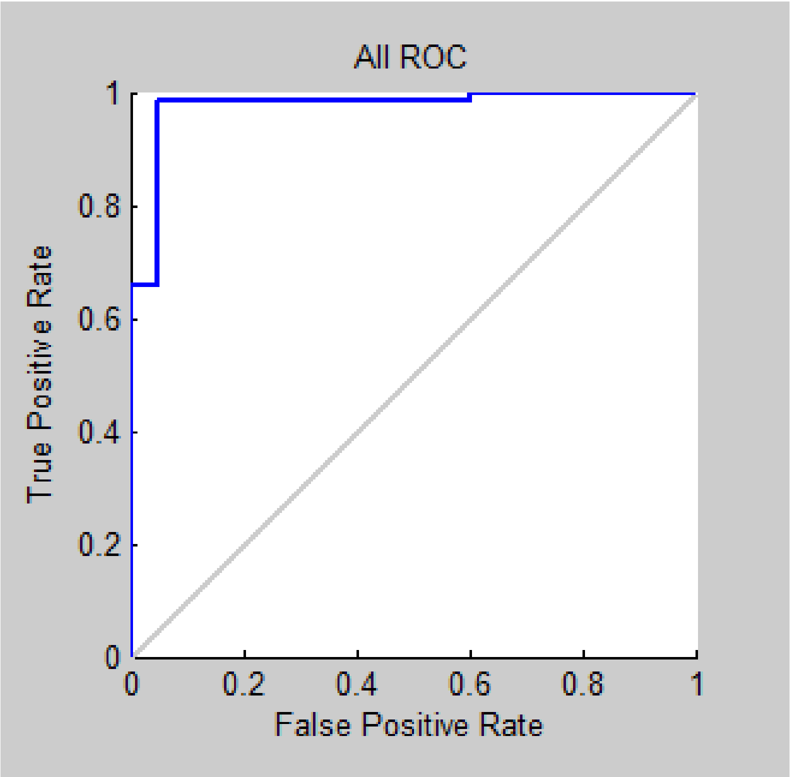


Figure-5.3: ROC Curve for LR

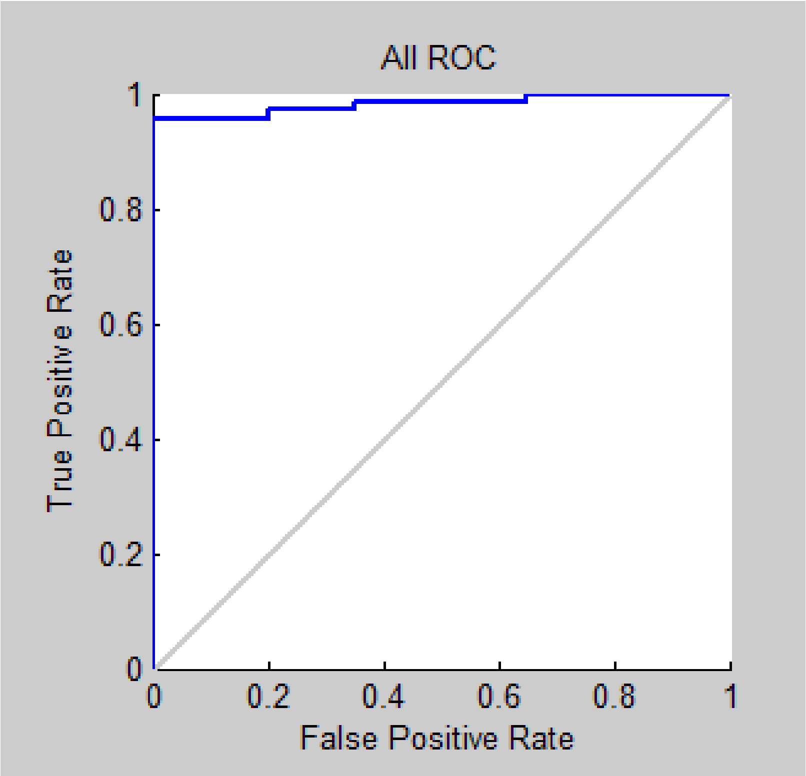


Figure-5.4: ROC Curve for ANN

The AUC values for the replications are given in the table below:

Table-5.6: AUC Values (%)

Repetition	LR	ANN
1	94.5	98.6
2	95.5	95.8
3	94.3	96.4
4	93.4	94.2
5	93.2	94.5
6	91	91.5
7	95.8	89.5
8	95.6	94.1
9	89.1	96.2
10	98.1	98
Average	94.05	94.88

In summary, our results show that, ANN performs better than LR in terms of both predictive and explanatory power. Thus it is suggested to use ANN in order to estimate the default probabilities of municipalities.

5.3.2. Calculating Guarantee Premium

The estimated default probabilities by using ANNs are used to calculate the guarantee premium. While calculating the premium, several methods which are Credit Default Swaps (CDS), Interest Rate Difference (IRD) and Expected Loss (EL) pricing are considered. The calculated premiums can be used as a benchmark for a fair guarantee premium.

In case UoT guarantees the debt obligation of a municipality to a Bank, the interest rate that the municipality faces will reduce. If we assume that UoT had the highest credit rating (the highest rating where the historical default probability is near zero), the interest rate paid by municipalities would be assumed to be the rate of 6 percent, and this rate can be called as risk-free interest rate. UoT wants to value the loan guarantee in order to manage its risk and determine the cash needed in the risk account.

The terms of the loan agreement require Municipality to make payments at the end of several periods. The terms of the loan guarantee require UoT to pay off Municipality's outstanding loan balance to Creditor if Municipality defaults. The amount of the obligation depends on when the default occurs according to the recovery rate of the municipality.

In relations with municipalities, UoT generally has a significant liability if Municipality defaults. The value of the loan guarantee would be the compensation demanded by UoT for taking this risk. If Municipality had to go out and purchase the loan guarantee from UoT, assuming perfect markets, the price of such a guarantee would equal the cost incurred by UoT in hedging the risk associated with the guarantee.

5.3.2.1. Valuation by CDS, IRD and EL

The value of the loan guarantee is calculated with using Credit Default Swap (CDS), Interest Rate Difference (IRD) and Expected Loss (EL) approximations. If UoT deposits the indicated percentage of the whole amount into the risk account, then the cash required of UoT in the future if Municipality default would be expected to be zero.

Firstly, the loan guarantee is valued as a CDS directly instead of pricing it within the market since we do not know where the municipalities fit on the ratings scale in the financial markets.

We made some assumptions before constructing our pricing model. We assume that the markets are complete, i.e. we assume that every asset in every state has an equilibrium price in a market. In order to hedge a replicating portfolio by trading in the risk-free loan and the underlying risky loan, complete market assumption needs to be made.

Another assumption we make is that the market rate of interest at which Municipality could borrow is unknown. For this exercise, we will assume that this rate cannot be ascertained directly. In other words, we assume that the Creditor does not quote an interest rate with and without the guarantee. As we do not have a quoted rate, we determine a proxy rate analytically by using default probabilities estimated by ANN, loss given default and risk-free interest rate.

Also, we assumed the spread between risk-free and risky loan is due to credit risk exclusively. Though the spread over risk-free rates may account for other risks rather than credit risk, for instance liquidity risk and tax considerations, we will ignore them.

Other assumptions being made are that the risk-free lending rate is 6 percent, there are no loan prepayments, and the loss-given-default of municipalities is 45 percent which is stated by the field experts in UoT.

In order to value the loan guarantee by using CDS pricing, we start with the last payment and work backwards to the initial payment. We work backwards because we need to know how much cash must be in the portfolio at the end of each period, so that the portfolio can be funded in the next period if Municipality does not default.

The actual MPEs for calculated guarantee premium with 3 different tools and actual losses for municipalities involved in test data can be shown in the Table-5.7. Error terms are multiplied by minus 1 to see if we have deficit or excess in the portfolio.

Municipalities having all transactions as defaulted or all transactions as non-defaulted are removed when calculating the guarantee premium. Since the face value of the loans and payment obligations of the remaining four municipalities are different, the weighted error terms for the portfolio is calculated and reported.

Table-5.7: MPEs for Calculated Guarantee Premium

	CDS	IRD	EL
MPE	5.39%	5.39%	-54.73%

As seen in the table above, CDS and IRD has same error terms when the risk-free interest rate is 6% and the IRS is zero. They overestimate the capital requirement and it leads to excess in the risk account. EL has a big error term since it underestimates the required guarantee premiums for the municipalities.

When estimating default probabilities, we showed that ANN outperforms LR. Although we reported the error terms when the default probabilities estimated by LR are used.

Table-5.8: MPEs with PD Values Estimated by LR

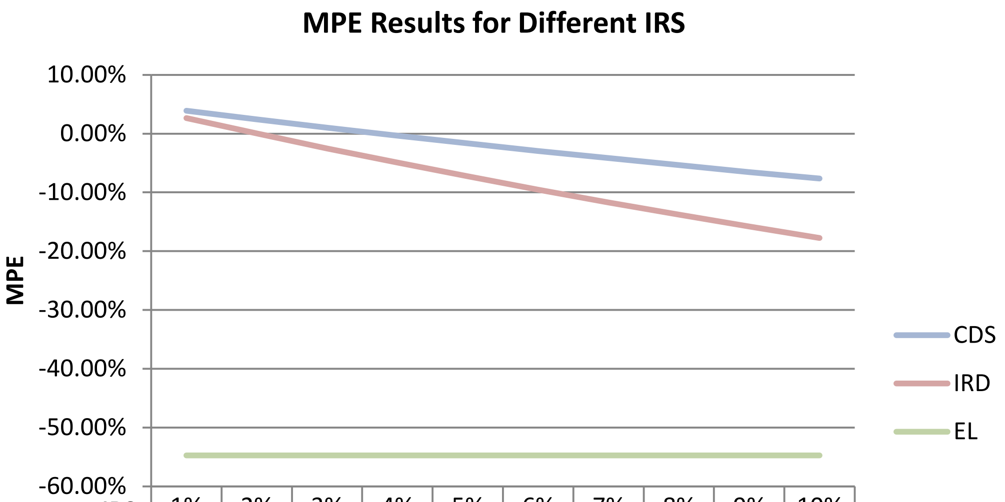
	CDS	IRD	EL
MPE	-7.83%	-7.83%	-62.74%

Error terms are slightly higher than the results while ANN is used to estimate the default probabilities.

5.4. Scenario Analysis and Stress Testing on Calculated Guarantee Premium

Scenario Analysis is widely used to see the effects of different level of parameters on the output. Stress testing is another term used by Basel Accord which refers to testing how strong the institutions in case of facing unforeseen values of different factors. It is now a regulatory requirement for large institutions and banks according to Basel Accord. We want to see what happens to our results and capital collected in the risk account by calculated guarantee premium under values changing PD, LGD, risk-free interest rate and IRS.

IRD method is actually estimation to CDS pricing and it is expected to become less accurate as Interest Rate Spread (IRS) increases. As we said in Chapter 4, it is assumed that the UoT borrows at the risk-free interest rate. IRS is defined by the Creditor. That is why; we need to test the IRS, too. Thus, the difference between CDS and IRD can be seen also. The results are shown in the figure below:

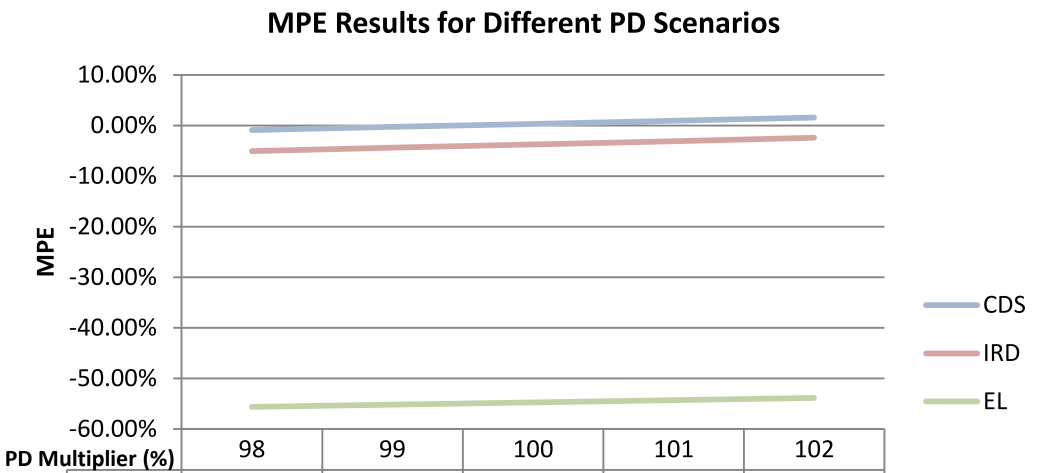


IRS	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%
CDS	3.88%	2.43%	1.02%	-0.34	-1.66	-2.94	-4.18	-5.37	-6.54	-7.66
IRD	2.65%	0.02%	-2.51	-4.95	-7.29	-9.54	-11.7	-13.8	-15.8	-17.7
EL	-54.7	-54.7	-54.7	-54.7	-54.7	-54.7	-54.7	-54.7	-54.7	-54.7

Figure-5.5: MPE Results for Different IRS Values

As we expect, EL Pricing does not affected since it only uses the risk-free interest rate. According to our results, the error terms have a decreasing trend when the interest rate difference increases but it is interesting that the error terms of IRD when the spread is 2% is better than the error terms of CDS. After the spread is higher than 2%, CDS pricing gives the best results.

Next, we want to see how our results react in case of default probabilities are increased. In order to see the PD effects on the difference between the results of CDS and IRD, IRS is assumed as 3.5% which is the current interest rate corridor applied by the Central Bank of Turkey on May, 2015. The effects of over and under estimated default probabilities are shown in the figure below:



PD Multiplier (%)	98	99	100	101	102
CDS	-0.91%	-0.29%	0.33%	0.94%	1.54%
IRD	-5.09%	-4.41%	-3.74%	-3.08%	-2.43%
EL	-55.63%	-55.18%	-54.73%	-54.28%	-53.82%

Figure-5.6: MPE Results for Estimated Different PD Values

As seen in the Figure-5.6, there is an increasing trend in capital collected when the PD increases. It means when PD increases we hold more capital in the risk account and cease the opportunity of investing the excess money collected.

As we said, the guarantee premium must be between 0.1% and 1% of the guaranteed or on-lent amount in accordance with the legislation. In this case, MPEs are much higher as seen in Table-5.9 and Table-5.10. Applying limit on guarantee premium causes huge losses. It can be logical to use a skewed function of default probability to determine the guarantee premium within a certain limit. Even though the upper limit is applied for the guarantee premium, still the guarantee fees collected from other institutions apart from municipalities need to compensate the deficit. If we assume that UoT does not reconstruct the debt of municipalities in case of default, removing limits on guarantee premium brings additional gain of 44.38% even though basic EL pricing is used. In case of more sophisticated tools such as CDS is used, the gain from the loss is increased to 93.49% when IRS is 0%.

Also, we mentioned that the Basel Accord requests financial institutions to maintain capital requirements. It is 12% in case of the related entity has lowest credit rating. MPE results are shown in the table below if 12% is applied as limit on the guarantee premium.

Table-5.9: MPEs for Calculated Guarantee Premium (IRS=0%)

	MPE		
	CDS	IRD	EL
1% Limit	-98.88%	-98.88%	-99.10%
12% Limit	-87.65%	-87.65%	-89.12%
No Limit	5.39%	5.39%	-54.73%

Table-5.10: MPEs for Calculated Guarantee Premium (IRS=3.5%)

	MPE		
	CDS	IRD	EL
1% Limit	-98.88%	-98.89%	-99.10%
12% Limit	-87.68%	-87.72%	-89.12%
No Limit	0.33%	-3.74%	-54.73%

In the study, the risk-free interest rate is assumed as 6%. The error terms for different risk-free interest rates are shown in the table below:

Table -5.11: MPEs for Different Risk-free Interest Rates

		IRS (%)					
		0			3.5		
		CDS	IRD	EL	CDS	IRD	EL
Risk-free Interest Rate (%)	2	11.11%	16.77%	-49.88%	5.37%	6.02%	-49.88%
	4	8.17%	10.84%	-52.41%	2.79%	0.95%	-52.41%
	6	5.39%	5.39%	-54.73%	0.33%	-3.74%	-54.73%
	8	2.75%	0.36%	-56.87%	-2.01%	-8.09%	-56.87%
	10	0.25%	-4.30%	-58.85%	-4.23%	-12.12%	-58.85%

The results show that the error terms of CDS and IRD pricing decreases while the error terms of EL pricing increases when the risk-free interest rate increases.

However, when IRS is 3.5%, the error terms start to increase after some point in the negative way which reflects the deficit in the risk account. In the figures below the error terms are presented.

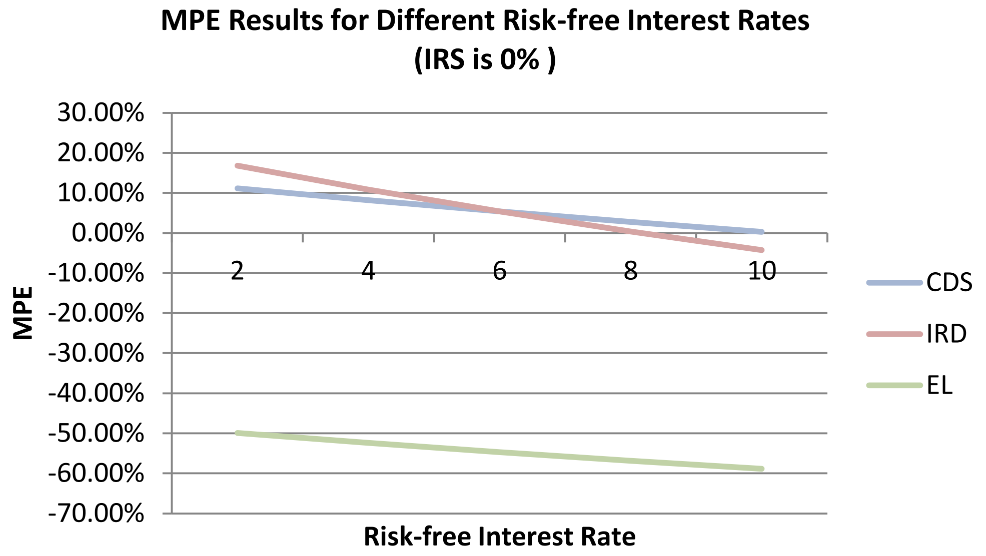


Figure-5.7: MPE Results for Different Risk-free Interest Rates–IRS is 0%

As seen in the Figure-5.7, the reaction of IRD pricing on risk-free interest rate is steeper than CDS pricing.

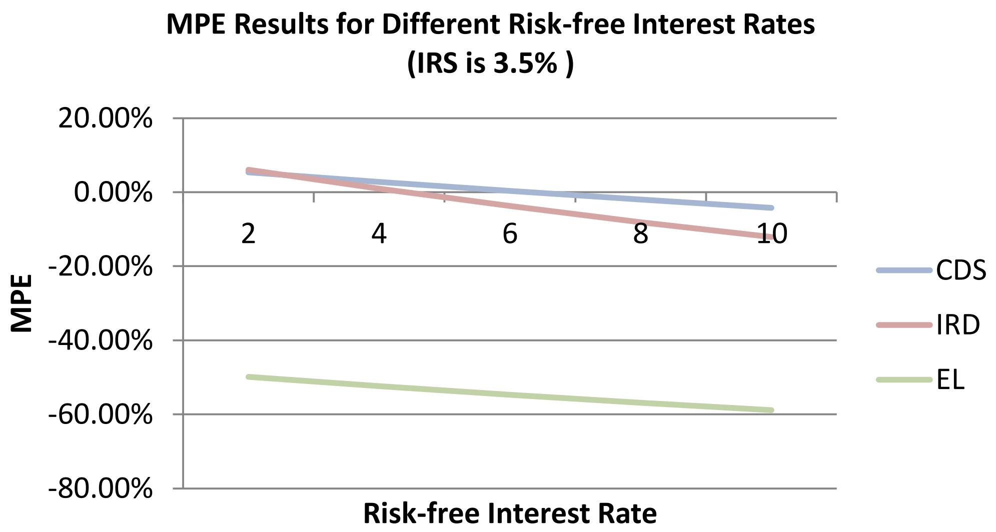


Figure-5.8: MPE Results for Different Risk-free Interest Rates–IRS is 3.5%

In the study, LGD is assumed as 45% in the direction of field experts' opinion. Although each municipality has different LGD, we examined LGD effects on MPE terms. Different LGD rates are evaluated where risk-free interest rate is 6% and IRS values for 0% and 3.5%. The results are shown in the table and figures below:

Table-5.12: MPEs for Different LGD rates

		IRS (%)					
		0			3.5		
		CDS	IRD	EL	CDS	IRD	EL
LGD (%)	35	3.68%	3.68%	-64.79%	-1.25%	-5.45%	-64.79%
	40	4.62%	4.62%	-59.76%	-0.38%	-4.51%	-59.76%
	45	5.39%	5.39%	-54.73%	0.33%	-3.74%	-54.73%
	50	6.03%	6.03%	-49.70%	0.92%	-3.10%	-49.70%
	55	6.56%	6.56%	-44.67%	1.42%	-2.57%	-44.67%

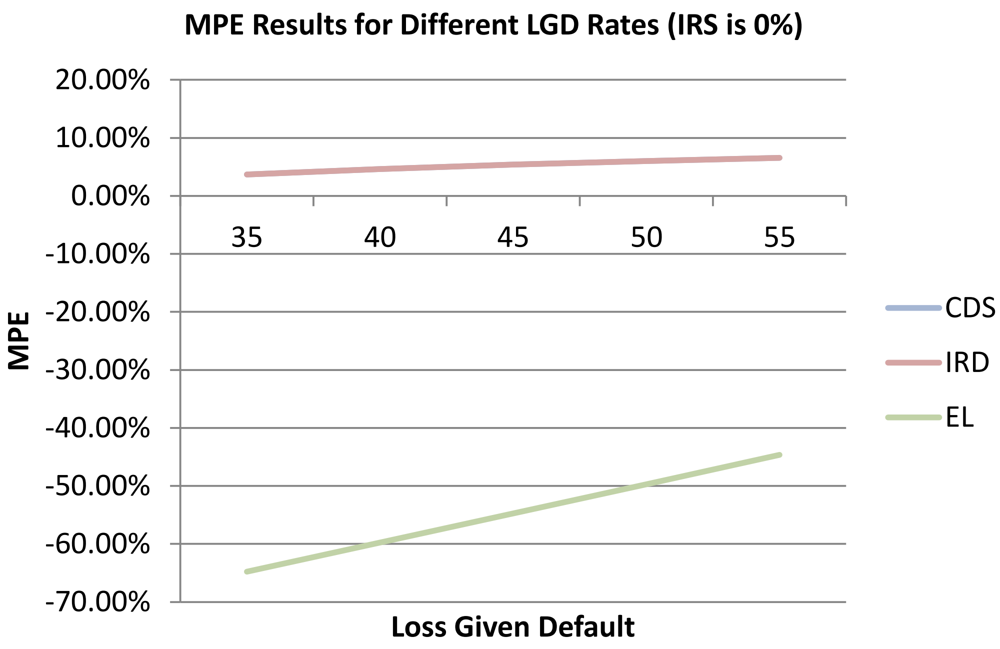


Figure-5.9: MPEs for Different LGD Rates–IRS is 0%

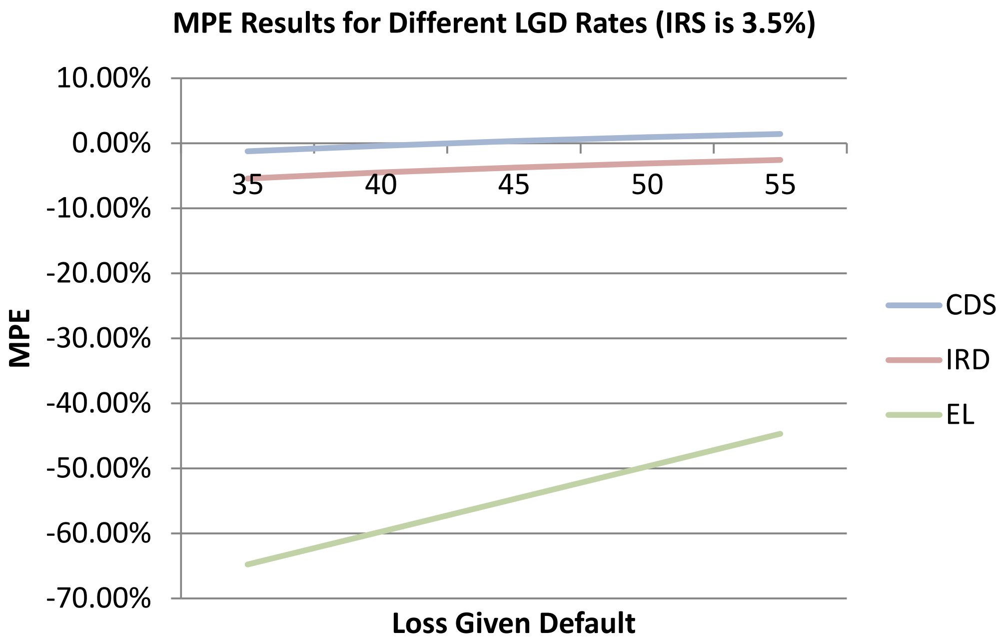


Figure-5.10: MPEs for Different LGD Rates–IRS is 3.5%

As seen from the results, as LGD increases, guarantee premiums and capital collected increases, and capital excess is observed after some point. Besides, increase in LGD rate gives lower error terms for EL pricing. The reason is that EL underestimates the guarantee premiums and increase in LGD rate gives higher guarantee premium collected in the risk account which is closer to the actual loss.

CHAPTER 6

CONCLUSION

In terms of financing projects with low-cost credits, guarantees have significant importance. The value of the guarantee is expected to increase with the credit risk of the related counterparty. In order to determine the fair guarantee premium, the specific features of the financial relationship between the related stakeholders need to be assessed and necessary adjustments need to be made.

As a result of this study, ANNs are suggested to be used to estimate the default probabilities of the municipalities. On the other hand, the explanatory variables are not easy to reveal since the neural network is recognized as a black box. In addition, using a proxy rate and CDS pricing, the guarantee premium calculation can be done more precisely. Especially, when the limits applied due to the current legislation is removed; the loss reduction can be significant.

In future studies, some of the points can be examined in detail. One of them is loss given default estimation. It is important and need to be estimated carefully. We assumed the LGD of the municipalities with expert opinion but the estimating LGD with constructing a model can give better approximations.

Definition of default can be included in the study. According to the Basel Accord, the default is defined if a payment is 60 days overdue and the lender official makes the judgment and reaches the conclusion that the payment is unlikely to be made in the future. Alternative definitions like this can be constructed and the results can be compared.

Put option can be used to calculate the fair guarantee premium since there is no need for the actual default probabilities if the complete market assumption is made. However, volatility of the debt payment power of the institution needs to be estimated as well as the risk-free interest rate.

Expert opinion for the entities can be incorporated with the current variables. In order to do this, additional variables such as Payment routine, Management’s prestige, Financial and managerial risk, Building ownership and Relations with financial institutions can be added to the model.

REFERENCES

Altman E.I., Frydman H., Kao D.L., “Introducing recursive partitioning for financial classification: The case of financial distress”, The Journal of Finance, 40:269–291, 1985.

Altman E.I., “Financial ratios, discriminant analysis and prediction of corporate bankruptcy”, The Journal of Finance, 23:589–609, 1968.

Biglova A., Ortobelli S., Fabozzi F.J., “Portfolio selection in the presence of systemic risk”, Journal of Asset Management 15, 285-299 2014.

Black F., and Scholes M., “The Pricing of Options and Corporate Liabilities.”Journal of Political Economy81 (3): 637–54, 1973.

Blum M., “Failing company discriminant analysis”, Journal of Accounting Re-search, 12(Spring):1–25, 1974.

Cames F. and Hill M., “Consumer credit scoring models: does the underlying probability distribution matters?”, Conference CEMAPRE, 2000.

Carling, K., "Corporate credit risk modeling and the macroeconomy", Journal of Banking and Finance, 2007.

Carling K., Jacobson T., Linde J. and Roszbach K., Journal of Banking and Finance, “Corporate credit risk modeling and the macro economy”, 2006.

Coats and Fant., “Recognizing financial distress patterns using a neural network tool”, Financial Management, Autumn:142–155, 1993.

Cohen, S., Doumpos, M., Neophytou, E. and Zopounidis, C., “Assessing Financial Distress where Bankruptcy is not an Option: An Alternative Approach for Local Municipalities”, Financial Engineering Laboratory, Technical University of Crete, July 2011.

Dambolena I.G. and Khoury S.J.. “Ratio stability and corporate failure”, Journal of Finance, 35(4):1017–1026, 1980.

Danenasa P., Garsva G., “Selection of Support Vector Machines based classifiers for credit risk domain”, Expert Systems with Applications, Volume 42, Issue 6, Pages 3194–3204, 2015.

Data on Treasury Receivables., Retrieved from: http://www.treasury.gov.tr/en-US/Stat-List?mid=738&cid=12&nm=684., June 30, 2015.

Dominguez D., González M., Serrano E., Rodríguez F.B., "Structured information in small-world neural networks", Phys. Rev. E 79, 021909, 2009.

Duda, R. O., Hart, P. E. and Stork, D. G., "Pattern Classification", John Wiley and Sons. Nov 1, 2000.

Elizalde A., "Credit Default Swap Valuation: An Application to Spanish Firms", May 2005.

Gehrlein W.V. and Wagner B.J., "A Two-Stage Least Cost Credit Scoring Model", Annals of Operations Research, 74:159–171, 1997.

Harrel, F., "Regression modeling strategies", Springer Science & Business Media, 2001.

Hayden E., "Are credit scoring models sensitive to different default definitions? evidence from the austrian market", SSRN Working Paper, 2003.

Hull J. and White A., "The Valuation of Credit Default Swap Options", September, 2002.

Jones, S. and Walker, R., "Explanators of local government distress", Abacus, 43(3), 396–418, 2007.

Kiviluoto K., "Predicting bankruptcies with the self-organizing map", Neurocomputing, 21:191–201, 1998.

Kleine, R., Kloha, P. and Weissert, C.S., "Monitoring local government fiscal health", Government Finance Review, 19(3), 18–23, 2003.

Kolesar P. Showers J.L., "A robust credit screening model using categorical data", Management Science, 31:123–133, 1985.

Lu C., Brabanter J. De, Van Huffel S., Vergote I. and Timmerman D., "Logistic Regression and Artificial Neural Networks for Classification of Overiaan Tumors", Technical Report, May 2001.

Merton, R. C. "An Analytic Derivation of the Cost of Deposit Insurance and Loan Guarantees: An Application of Modern Option Pricing Theory."Journal of Banking and Finance1:3-11. 1977.

Merton, R. C. "Theory of Rational Option Pricing."Bell Journal of Economics and Management Science4 (1): 141–83. 1973.

Myers J.H. and Frogy E.W., "The development of numerical credit evaluation systems", Journal of American Statistics Association, 58(September):799–806, 1963.

Pompe P. and Feelders A., “Using machine learning, neural networks, and statistics to predict corporate bankruptcy”, Microcomputers in Civil Engineering, 12:267–276, 1997.

Schurman, G., “Valuing Loan Guarantees”, A Professional Development Journal for the Consulting Disciplines, 2010.

Sinkkonen J., Kaski S. and Peltonen J., “Bankruptcy analysis with self-organizing maps in learning metrics”, IEEE Transactions on Neural Networks, 12(4):936–947, 2001.

Tam K. and Kiang M., “Managerial application of neural networks: the case of bank failure predictions”, Management Science, 38(7):926–947, 1992.

Wiginton J.C., “A note on the comparison of logit and discriminant models of consumer credit behavior”, Journal of Financial and Quantitative Analysis, 15:757–770, 1980.

Wilcox J.W., “A prediction of business failure using accounting data”, Journal of Accounting Research, 11, 1973.

Wu L., “A Primer on Credit Default Swaps”, Baruch College and Bloomberg LP, Beijing, China, 2008.

Yu L., Lai K.K., Wang S., “An Evolutionary Programming Based Knowledge Ensemble Model for Business Risk Identification”, Soft Computing Applications in Business, Studies in Fuzziness and Soft Computing Volume 230, pp 57-72, 2008.

Zhiwang Z., Guangxia G. and Yong S., “Credit risk evaluation using multi-criteria optimization classifier with kernel, fuzzification and penalty factors”, European Journal of Operational Research, 2014.

Zalewska A., “Modelling the Price of a Credit Default Swap”, Master’s Thesis Department of Numerical Analysis at the Scientific Computing International Master Program, Royal Institute of Technology, 2004.

Zhou, X., "Credit risk evaluation with kernel based affine subspace nearest points learning method", Expert Systems with Applications, 2011.

APPENDICES

Appendix A: Flow Chart of Foreign Finance Providing Process

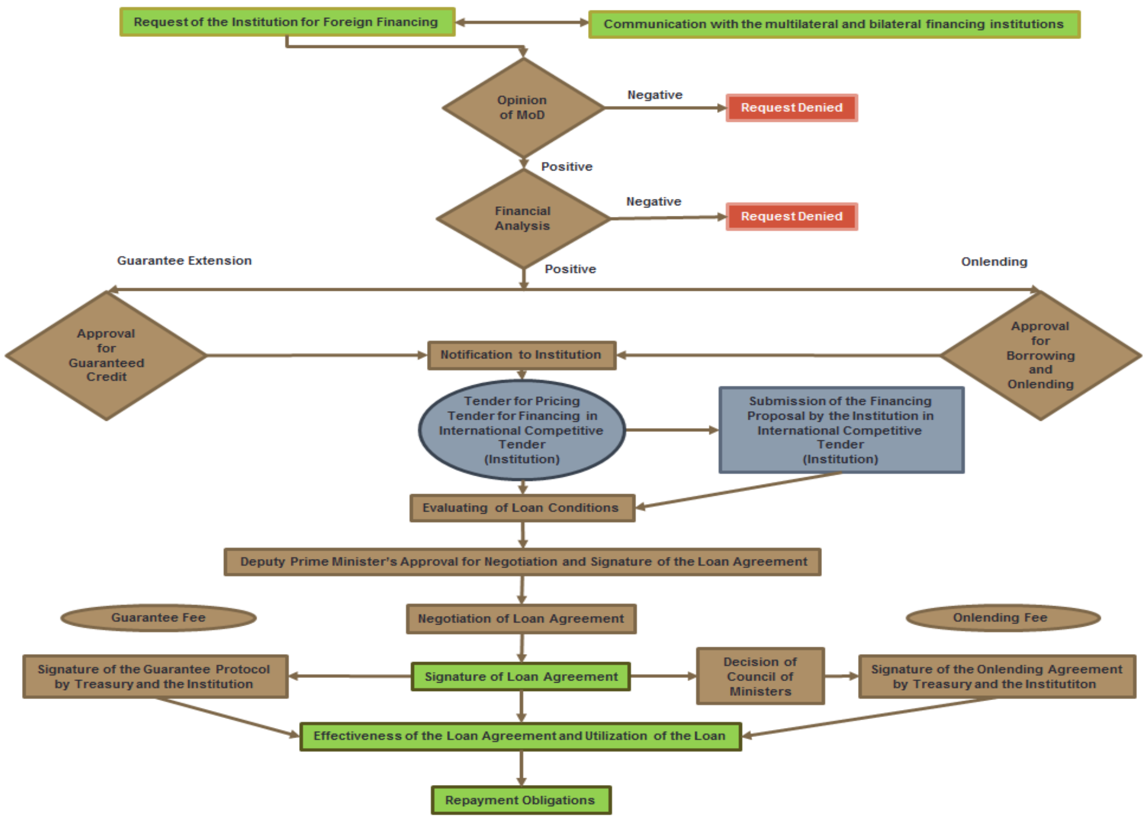


Figure-A.1: Flow Chart of Foreign Finance Providing Process

Appendix B: Correlation Matrix of the Input Variables

	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16	v17	v18	v19	v20	v21	v22	v23	v24	v25
v1		-0,98	-0,21	0,25	0,19	0,09	-0,12	0,21	0,29	-0,20	0,17	0,12	0,14	0,10	-0,03	-0,12	-0,05	-0,07	-0,01	-0,10	-0,12	-0,03	0,06	-0,01	-0,10
v2	-0,98		0,22	-0,22	-0,19	-0,09	0,11	-0,21	-0,28	0,17	-0,17	-0,12	-0,12	-0,11	-0,01	0,03	0,03	0,07	-0,02	0,11	0,11	0,05	-0,03	0,04	0,10
v3	-0,21	0,22		-0,26	-0,09	-0,14	-0,07	-0,03	-0,25	-0,14	-0,03	-0,20	0,40	0,16	0,00	-0,10	0,06	0,28	-0,08	-0,04	0,23	-0,01	0,23	0,02	-0,05
v4	0,25	-0,22	-0,26		0,61	0,09	0,16	0,15	0,93	0,00	0,36	0,58	-0,09	-0,08	-0,40	-0,45	-0,17	-0,10	-0,25	0,13	-0,02	0,26	0,29	-0,12	0,02
v5	0,19	-0,19	-0,09	0,61		0,02	-0,16	0,17	0,43	-0,01	0,27	0,53	0,01	0,02	-0,25	-0,23	-0,35	-0,09	-0,13	0,02	-0,18	0,22	0,37	-0,12	0,02
v6	0,09	-0,09	-0,14	0,09	0,02		0,47	-0,06	0,05	0,43	0,12	-0,03	-0,32	-0,42	-0,04	-0,08	-0,34	-0,01	0,12	0,03	-0,18	-0,22	-0,21	-0,10	-0,06
v7	-0,12	0,11	-0,07	0,16	-0,16	0,47		-0,05	0,16	0,46	0,12	0,24	-0,27	-0,33	-0,04	0,04	0,12	0,05	-0,02	0,19	0,24	-0,32	-0,38	0,12	0,07
v8	0,21	-0,21	-0,03	0,15	0,17	-0,06	-0,05		0,16	-0,10	0,41	0,23	-0,15	-0,11	-0,08	-0,12	-0,11	0,23	0,18	0,00	0,04	0,02	-0,05	-0,15	0,17
v9	0,29	-0,28	-0,25	0,93	0,43	0,05	0,16	0,16		-0,06	0,46	0,64	0,03	0,01	-0,34	-0,30	-0,16	-0,10	-0,26	0,14	0,04	0,31	0,27	-0,14	0,01
v10	-0,20	0,17	-0,14	0,00	-0,01	0,43	0,46	-0,10	-0,06		0,12	0,16	-0,42	-0,40	0,01	0,02	-0,23	0,04	0,13	-0,01	0,03	-0,32	-0,50	0,03	-0,21
v11	0,17	-0,17	-0,03	0,36	0,27	0,12	0,12	0,41	0,46	0,12		0,60	-0,12	0,13	-0,17	-0,05	-0,03	0,06	0,02	0,20	0,13	0,06	-0,08	-0,16	0,02
v12	0,12	-0,12	-0,20	0,58	0,53	-0,03	0,24	0,23	0,64	0,16	0,60		-0,13	0,09	-0,18	-0,12	0,12	-0,15	-0,17	0,07	0,00	-0,02	-0,10	0,07	0,05
v13	0,14	-0,12	0,40	-0,09	0,01	-0,32	-0,27	-0,15	0,03	-0,42	-0,12	-0,13		0,33	0,04	-0,15	0,14	0,02	-0,14	0,06	0,15	0,27	0,29	0,07	-0,15
v14	0,10	-0,11	0,16	-0,08	0,02	-0,42	-0,33	-0,11	0,01	-0,40	0,13	0,09	0,33		0,15	0,19	0,64	0,04	-0,05	-0,02	0,23	0,20	0,17	0,02	0,04
v15	-0,03	-0,01	0,00	-0,40	-0,25	-0,04	-0,04	-0,08	-0,34	0,01	-0,17	-0,18	0,04	0,15		0,43	0,33	-0,03	0,13	-0,09	-0,04	-0,16	-0,23	0,01	0,02
v16	-0,12	0,03	-0,10	-0,45	-0,23	-0,08	0,04	-0,12	-0,30	0,02	-0,05	-0,12	-0,15	0,19	0,43		0,31	-0,03	0,15	-0,06	0,05	-0,12	-0,25	-0,07	0,11
v17	-0,05	0,03	0,06	-0,17	-0,35	-0,34	0,12	-0,11	-0,16	-0,23	-0,03	0,12	0,14	0,64	0,33	0,31		-0,05	-0,07	0,03	0,24	-0,08	-0,14	0,21	0,18
v18	-0,07	0,07	0,28	-0,10	-0,09	-0,01	0,05	0,23	-0,10	0,04	0,06	-0,15	0,02	0,04	-0,03	-0,03	-0,05		0,65	-0,07	0,42	0,13	0,02	0,18	-0,21
v19	-0,01	-0,02	-0,08	-0,25	-0,13	0,12	-0,02	0,18	-0,26	0,13	0,02	-0,17	-0,14	-0,05	0,13	0,15	-0,07	0,65		-0,08	0,00	-0,10	-0,25	0,21	-0,22
v20	-0,10	0,11	-0,04	0,13	0,02	0,03	0,19	0,00	0,14	-0,01	0,20	0,07	0,06	-0,02	-0,09	-0,06	0,03	-0,07	-0,08		0,05	-0,01	-0,07	-0,03	0,11
v21	-0,12	0,11	0,23	-0,02	-0,18	-0,18	0,24	0,04	0,04	0,03	0,13	0,00	0,15	0,23	-0,04	0,05	0,24	0,42	0,00	0,05		0,40	-0,04	-0,01	-0,02
v22	-0,03	0,05	-0,01	0,26	0,22	-0,22	-0,32	0,02	0,31	-0,32	0,06	-0,02	0,27	0,20	-0,16	-0,12	-0,08	0,13	-0,10	-0,01	0,40		0,48	0,02	-0,05
v23	0,06	-0,03	0,23	0,29	0,37	-0,21	-0,38	-0,05	0,27	-0,50	-0,08	-0,10	0,29	0,17	-0,23	-0,25	-0,14	0,02	-0,25	-0,07	-0,04	0,48		0,01	0,12
v24	-0,01	0,04	0,02	-0,12	-0,12	-0,10	0,12	-0,15	-0,14	0,03	-0,16	0,07	0,07	0,02	0,01	-0,07	0,21	0,18	0,21	-0,03	-0,01	0,02	0,01		-0,25
v25	-0,10	0,10	-0,05	0,02	0,02	-0,06	0,07	0,17	0,01	-0,21	0,02	0,05	-0,15	0,04	0,02	0,11	0,18	-0,21	-0,22	0,11	-0,02	-0,05	0,12	-0,25	

Figure-A.2: Correlation Matrix of the Input Variables

v2, v4, v12, v14, v19 are removed from the data set.

Appendix C: The Performance of Topologies with Different Number of Nodes in the Hidden Layer

Table-A.1: Performance of Topologies (Nodes between 3 and 124)

Number of Nodes	3	14	25	36	47	58	69	80	91	102	113	124
MAE	1,02%	0,82%	1,76%	1,69%	1,66%	1,45%	1,28%	1,31%	1,42%	1,55%	1,60%	1,53%
	1,55%	1,54%	1,30%	1,26%	1,24%	1,30%	1,34%	1,22%	1,04%	0,87%	0,80%	0,76%
	0,77%	0,79%	0,85%	0,80%	0,90%	0,81%	0,95%	1,01%	1,26%	1,28%	1,34%	1,33%
	1,32%	1,34%	1,45%	1,50%	1,31%	1,32%	1,22%	1,18%	1,01%	0,94%	0,93%	1,00%
Average	**1,17%**	**1,12%**	**1,34%**	**1,31%**	**1,28%**	**1,22%**	**1,20%**	**1,18%**	**1,18%**	**1,16%**	**1,17%**	**1,16%**
MSE	0,46%	0,35%	0,84%	0,75%	0,75%	0,66%	0,59%	0,58%	0,73%	0,79%	0,91%	0,86%
	0,88%	0,88%	0,77%	0,76%	0,74%	0,77%	0,82%	0,78%	0,61%	0,54%	0,42%	0,41%
	0,41%	0,43%	0,45%	0,43%	0,49%	0,43%	0,45%	0,48%	0,61%	0,61%	0,63%	0,62%
	0,61%	0,61%	0,73%	0,74%	0,66%	0,65%	0,61%	0,59%	0,50%	0,47%	0,45%	0,47%
Average	**0,59%**	**0,57%**	**0,70%**	**0,67%**	**0,66%**	**0,63%**	**0,62%**	**0,61%**	**0,61%**	**0,60%**	**0,60%**	**0,59%**
MAE (PCA is applied)	0,68%	0,57%	0,66%	0,51%	1,09%	1,30%	1,19%	1,26%	1,32%	1,20%	1,19%	1,15%
	1,21%	1,21%	1,18%	1,24%	1,08%	0,99%	1,09%	1,06%	1,11%	1,16%	1,09%	1,03%
	1,09%	1,33%	1,36%	1,33%	1,34%	1,39%	1,39%	1,32%	1,18%	1,13%	1,14%	1,39%
	1,30%	1,11%	1,13%	1,14%	1,10%	1,05%	1,01%	1,11%	1,19%	1,25%	1,29%	1,12%
Average	**1,07%**	**1,06%**	**1,08%**	**1,06%**	**1,15%**	**1,18%**	**1,17%**	**1,19%**	**1,20%**	**1,19%**	**1,18%**	**1,17%**
MSE (PCA is applied)	0,39%	0,31%	0,43%	0,41%	0,68%	0,72%	0,68%	0,74%	0,76%	0,70%	0,70%	0,68%
	0,71%	0,70%	0,68%	0,70%	0,58%	0,53%	0,58%	0,54%	0,62%	0,64%	0,60%	0,56%
	0,57%	0,70%	0,71%	0,71%	0,71%	0,73%	0,70%	0,68%	0,54%	0,54%	0,53%	0,66%
	0,64%	0,55%	0,55%	0,55%	0,54%	0,52%	0,51%	0,53%	0,55%	0,56%	0,58%	0,48%
Average	**0,58%**	**0,56%**	**0,59%**	**0,59%**	**0,63%**	**0,63%**	**0,62%**	**0,62%**	**0,62%**	**0,61%**	**0,60%**	**0,60%**

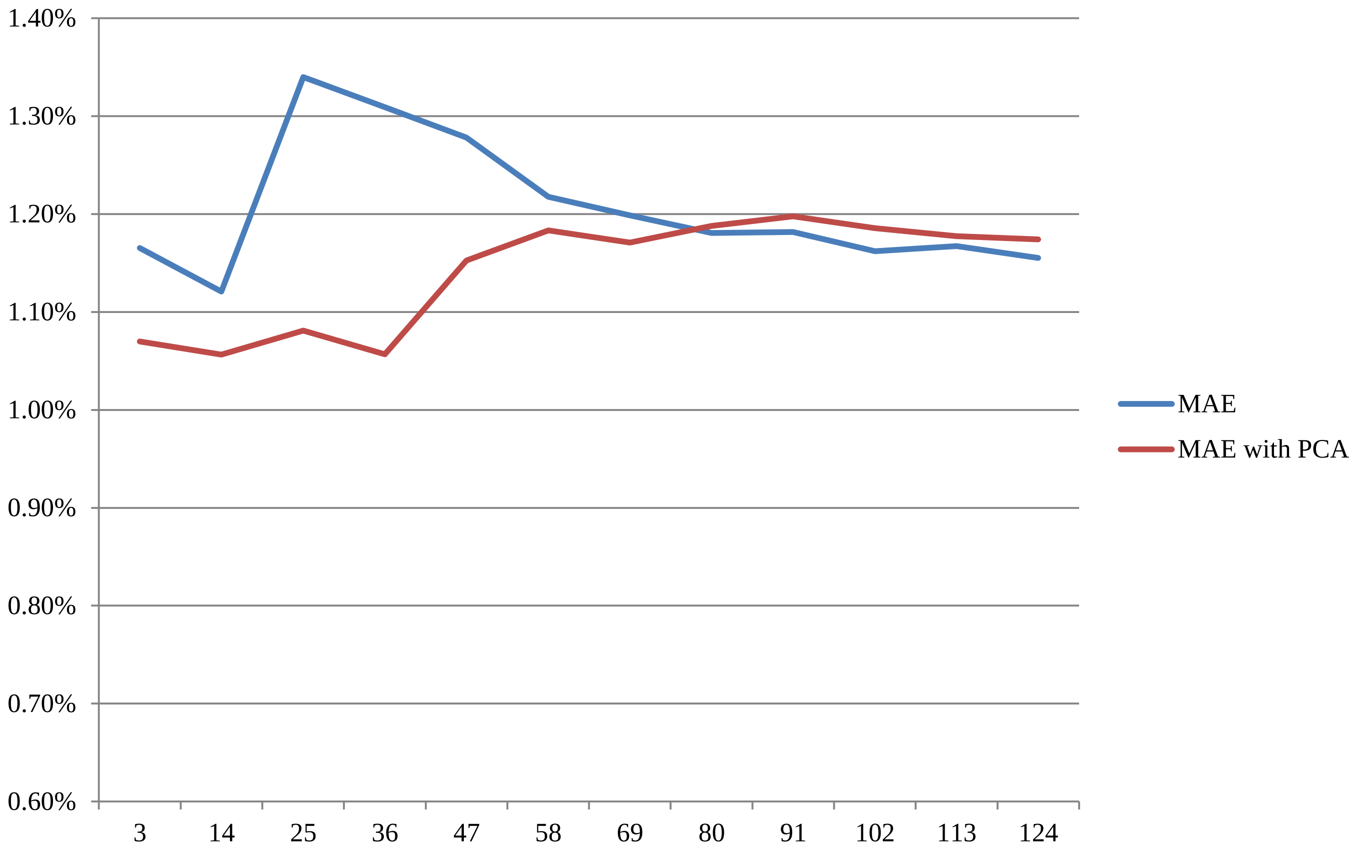


Figure-A.3: Performance of Different Topologies in terms of MAE

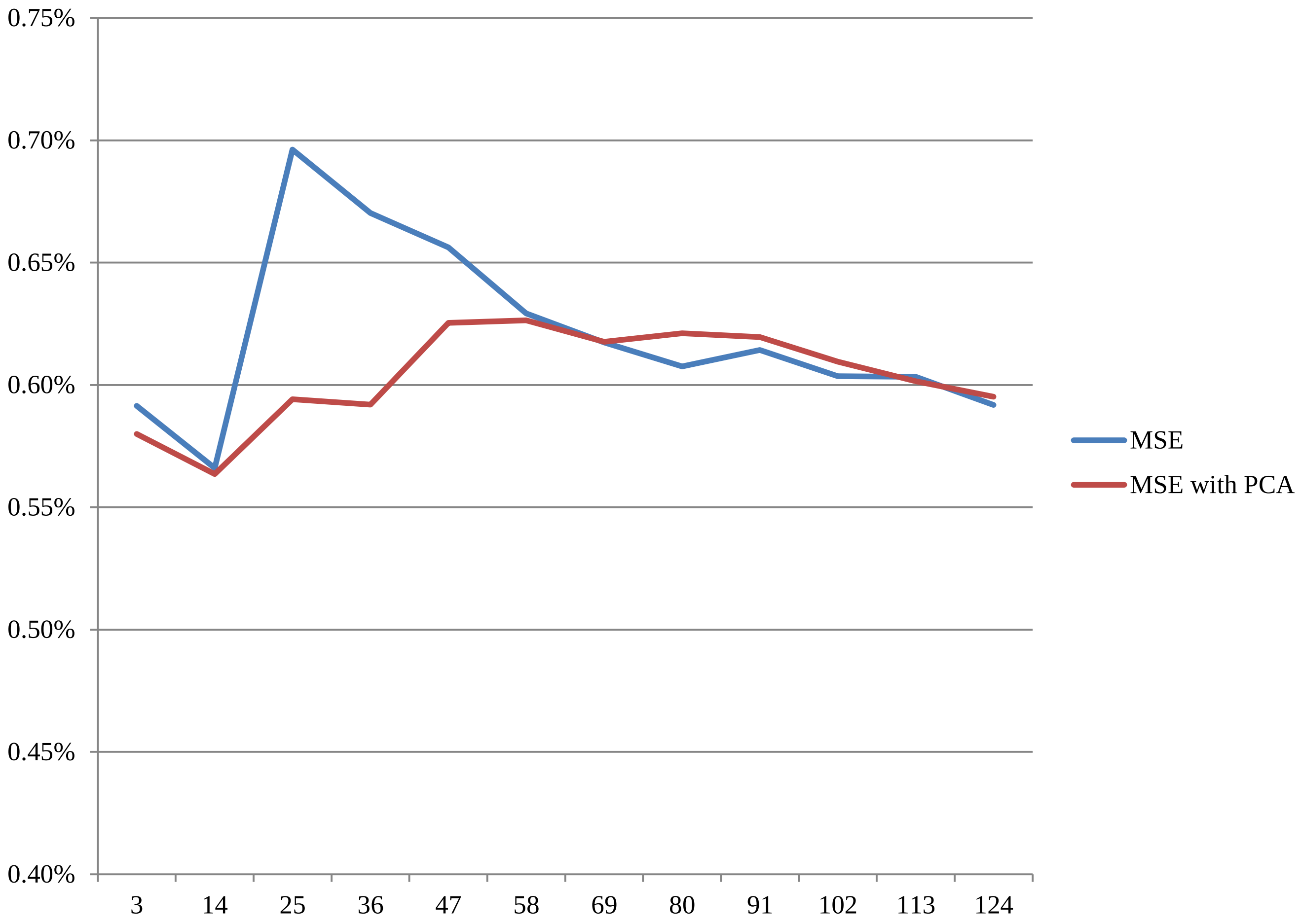


Figure-A.4: Performance of Different Topologies in terms of MSE

Table-A.2: Performance of Topologies (Nodes between 8 and 18)

Number of Nodes	8	10	12	14	16	18
MAE	0,69%	0,58%	1,93%	3,38%	3,73%	4,20%
	5,23%	4,23%	4,67%	3,66%	4,68%	4,68%
	5,63%	4,64%	6,09%	5,87%	4,27%	4,30%
	3,88%	4,44%	3,85%	4,48%	5,60%	5,50%
Average	**3,86%**	**3,47%**	**4,13%**	**4,35%**	**4,57%**	**4,67%**
MSE	0,31%	0,28%	0,88%	2,29%	2,37%	2,45%
	2,92%	2,49%	2,64%	1,62%	2,24%	2,24%
	3,31%	2,93%	3,73%	3,62%	2,73%	2,75%
	1,93%	2,18%	1,67%	1,86%	3,03%	3,02%
Average	**2,12%**	**1,97%**	**2,23%**	**2,35%**	**2,59%**	**2,62%**
MAE (PCA is applied)	1,55%	0,97%	1,56%	1,50%	1,58%	2,02%
	1,98%	1,67%	2,05%	1,98%	2,60%	2,46%
	3,30%	4,98%	4,48%	5,03%	4,36%	4,86%
	4,11%	2,89%	3,71%	3,26%	3,41%	2,49%
Average	**2,73%**	**2,63%**	**2,95%**	**2,95%**	**2,99%**	**2,96%**
MSE (PCA is applied)	0,81%	0,48%	0,94%	0,89%	0,94%	1,10%
	1,10%	0,93%	1,03%	1,02%	1,21%	1,33%
	2,34%	3,32%	3,05%	3,24%	2,96%	2,95%
	1,94%	1,13%	1,47%	1,37%	1,53%	1,16%
Average	**1,55%**	**1,46%**	**1,62%**	**1,63%**	**1,66%**	**1,63%**

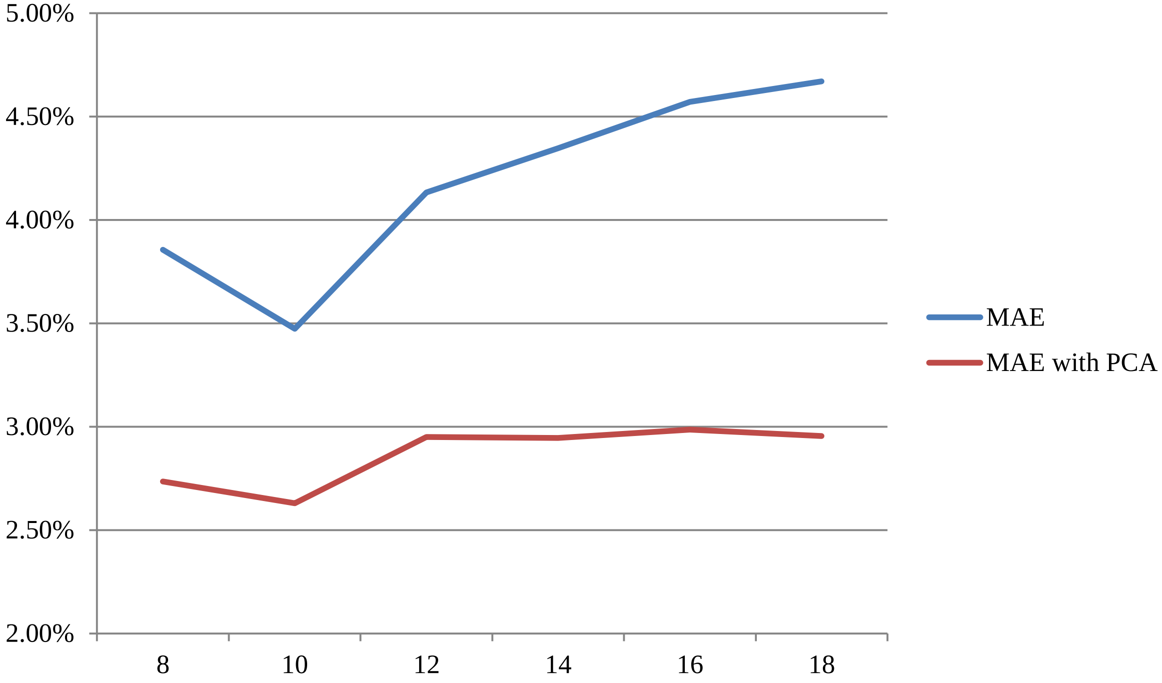


Figure-A.5: Performance of Different Topologies in terms of MAE-2

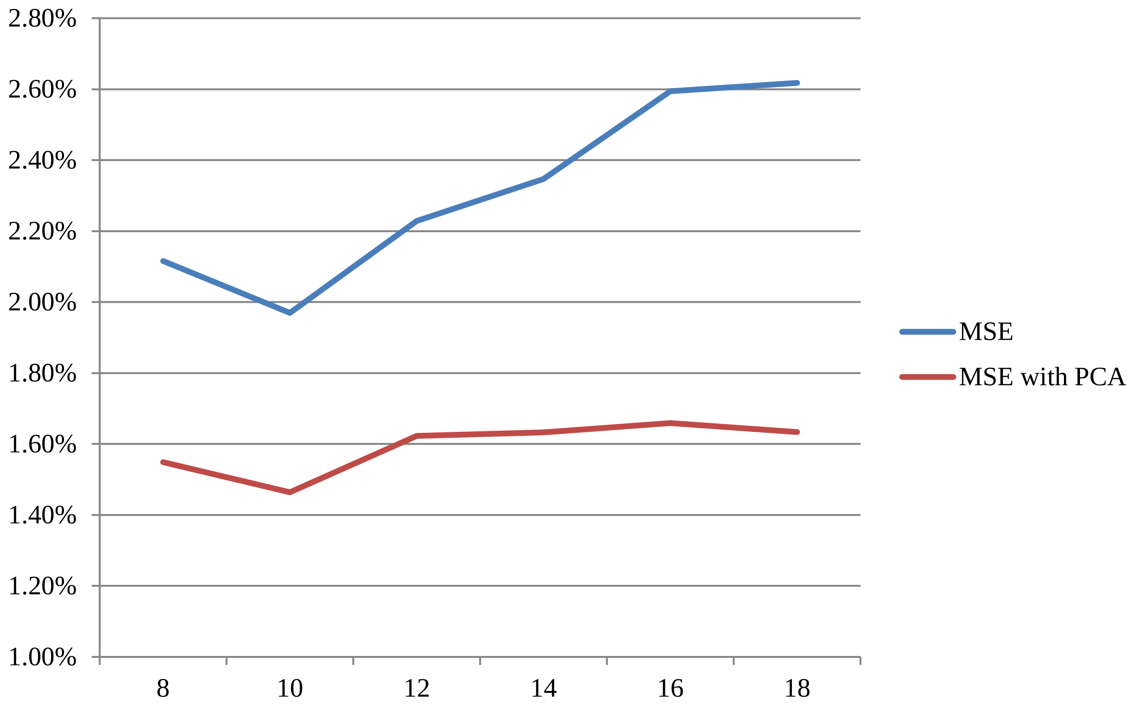


Figure-A.6: Performance of Different Topologies in terms of MSE-2

Since the data division is random, error terms are little different from the table above. According to these results, the topology consisting of 10 nodes in the hidden layer is assumed to be best topology and this topology is used to estimate the default probabilities. Another result shown in the tables is that applying PCA gives better results in almost every case.

Appendix D: The Performance of the Models

Table-A.3: The Performance of the Models

	Replication	1	2	3	4	5	6	7	8	9	10	Average
Logistic Regression	MAE for Validation Data	7.41%	6.05%	12.10%	6.25%	7.41%	7.41%	5.88%	5.56%	7.41%	11.11%	7.66%
	MAE for Overall	1.48%	0.86%	1.73%	1.14%	1.48%	1.48%	1.12%	1.11%	1.48%	2.22%	**1.41%**
	MSE for Validation Data	7.41%	5.87%	11.74%	6.25%	7.41%	7.41%	5.88%	5.56%	7.41%	11.11%	7.60%
	MSE for Overall	1.48%	0.84%	1.68%	1.14%	1.48%	1.48%	1.12%	1.11%	1.48%	2.22%	**1.40%**
Logistic Regression (PCA is applied)	MAE for Validation Data	7.14%	7.41%	6.05%	8.33%	9.09%	8.07%	9.52%	7.69%	9.52%	8.33%	8.12%
	MAE for Overall	1.16%	1.48%	0.86%	1.52%	1.20%	1.15%	1.55%	1.18%	0.84%	1.52%	**1.25%**
	MSE for Validation Data	7.14%	7.41%	5.87%	8.33%	9.09%	7.82%	9.52%	7.69%	9.52%	8.33%	8.07%
	MSE for Overall	1.16%	1.48%	0.84%	1.52%	1.20%	1.12%	1.55%	1.18%	0.84%	1.52%	**1.24%**
ANN	MAE for Validation Data	0.80%	0.72%	0.92%	2.12%	1.30%	1.85%	1.11%	1.74%	0.01%	1.43%	1.20%
	MAE for Test Data	2.80%	2.02%	0.65%	2.46%	2.19%	1.30%	2.22%	1.78%	3.30%	1.90%	2.06%
	MAE for Overall	1.80%	0.59%	0.70%	1.37%	1.24%	1.40%	1.11%	1.27%	0.45%	1.29%	**1.12%**
	MSE for Validation Data	0.08%	0.24%	0.31%	0.99%	1.11%	0.63%	1.11%	0.45%	0.56%	0.46%	0.59%
	MSE for Test Data	3.05%	1.75%	0.45%	1.39%	1.27%	0.90%	2.22%	0.52%	2.78%	0.94%	1.53%
	MSE for Overall	2.10%	0.50%	0.52%	0.57%	0.91%	0.51%	1.11%	0.86%	0.77%	0.53%	**0.84%**
ANN (PCA is applied)	MAE for Validation Data	2.07%	0.54%	1.31%	1.44%	2.56%	0.76%	0.77%	1.04%	0.90%	1.38%	1.28%
	MAE for Test Data	1.85%	2.20%	3.37%	3.59%	1.79%	1.26%	1.11%	0.92%	3.10%	1.23%	2.04%
	MAE for Overall	1.44%	0.66%	0.96%	1.89%	1.77%	0.74%	0.67%	0.72%	1.17%	0.96%	**1.10%**
	MSE for Validation Data	0.94%	0.26%	0.76%	0.65%	1.28%	0.18%	0.28%	0.47%	0.17%	0.63%	0.56%
	MSE for Test Data	0.72%	2.17%	2.11%	2.75%	0.71%	1.12%	1.05%	0.36%	2.31%	0.48%	1.38%
	MSE for Overall	0.52%	0.65%	0.89%	1.04%	0.72%	0.68%	0.52%	1.01%	0.70%	0.73%	**0.75%**