Credit Risk Modeling for Multilateral Lenders

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To my Mother and Sister for their support

Abstract

Financial crashes, bubbles, panic in the banking industry, currency crises and even sovereign defaults continue to occur periodically. Therefore when international or multilateral lenders contemplate on lending credit to customers who are located in different countries, they require a meticulous method of analysing every aspect to select the best customers, amongst numerous credit proposals from different countries. Moreover, while lending to selected customers, multilateral lenders need to take into account and consider the risk premium in their pricing methodology. Even after having selected sound customers, one should not neglect adequate loan loss provisions in order to safeguard themselves against unexpected changes in financial situations of customers. This may result in credit default. Although several credit scoring methodologies exist for calculating the risk of individuals and corporate customers, most of these methodologies are based on default history and there appears to be a lack of an appropriate methodology when faced with minimal credit default history. Usually, financial institutions and very large corporations are characterised by nil or a very low default history. Following this introduction, this dissertation aims to contribute towards these aspects in the form of three self-contained essays. The first chapter is concerned with determining the main factors which affect the financial health of financial institutions. More specifically, this is undertaken by employing the two-way panel model and data from financial institutions in several Asian countries. The study attempts to determine bank specific and macro level factors affecting the financial soundness of these financial institutions. In the second chapter by following a similar approach of analysis, this study attempts to detect the main determinants of financial health for very large corporations. These corporations are another group of customers for multilateral lenders. In this case, data from very large corporations in Eastern European countries which are characterised by their in-transition economies are employed. Considering the dissertation's findings that are supportive of existing literature, the third chapter addresses the design of two credit scoring/rating models employing fuzzy logic methodology and based upon results from previous chapters. The scoring/rating results of the two models are then analysed in comparison with the Capital Intelligence rating agency and stock exchange market performance results to assess robustness. This proves the relative robustness of our designed models. Overall, this thesis not only combines and investigates topical issues; moreover, it does so employing various techniques with the intention to contribute on the methodological level. The study is concluded by highlighting policy implications by providing direction for future research.

Contents

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For any errors or inadequacies that may remain in this work, of course the responsibility is entirely my own.

Declaration

I declare that, except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution. The copyright of this thesis rests with the author. Due acknowledgement must always be made of the use of any materials contained in, or derived from, this thesis.

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Scope of analysis

In recent years, finance officers and bankers have faced numerous challenges all over the world. These challenges primarily relate to the complexity of financial markets, as a result of growing demand for financing. In this regard, possessing knowledge of such complicated financial environments force the financiers to examine and find appropriate tools for measuring losses which may arise in worst case scenarios. This can be done through measuring the major risks in banking sector named market risk, operational risk, liquidity risk and credit risk. As the major operation of banks and financial institutions (FI) include lending activities[1] therefore, credit risk is one of the most important risk in banking system. Its negative impact on FI's performance is significant in worst case scenarios. For this reason, measuring the risk and keeping adequate provision, based on those calculations, is a must for every FI, to safeguard against losses which may arise when faced with non-performing loans[2]. In this regard, during the recent three decades, risk management and specially credit risk management has attracted many academics as well as researchers from the financial sector.

[1] Loans constitute the bulk of FIs asset size (see Table 1.1 for more information)

[2] Loans with delayed repayments of more than 90 days based on international standards

Credit Risk is defined as the risk of loss of principal or loss of a financial return resulting from a borrower's failure to repay a loan or to meet an agreed obligations. Credit risk arises and can be expected when a borrower does not meet their obligation in relation to future cash flows. Therefore, there is uncertainty over the borrower's financial performance in the future. As a result, in recent years, financiers seek tools and means to enable them to calculate the borrower's credit worthiness. A suitable credit limit can then be defined, risk based pricing can be set and subsequently adequate loan loss provisions can be kept to safeguard against the possible losses, in case the customers' obligations are not met.

As stated by Shojai and Feiger (2009) 2007 financial crises originated due to the inappropriate due diligence of mortgage borrowers by financial institutions and the over securitisation of such loans by transferring ownership to those mortgaged loans to other investor companies (usually the new investors were unaware of the quality of such loans, credit risk and the borrower's credit worthiness). Therefore, as banks no longer played a role as the assessors of due diligences, the role of rating customers was left to rating agencies[3]. On most occasions, neither are individuals or corporations rated by rating institutions nor does a complete/true picture of the customers' financial health exist. The "true picture" and information of the customers financial health was always held with the issuing bank which no longer cared about collecting or updating such information since the loans were already being sold to other investors. It would appear that the major problem commenced when changes and adjustments were made to house prices. (see Shojai and Feiger (2009) for more details).

With this introduction, which demonstrates that a lack of diligence and careful analysis by banks and financial institutions are considered as the major causes of the recent financial crises, the importance of robust credit decisions has been clarified. However, in order to make sound credit decisions, every creditor must have suitable instruments

[3]Credit rating agencies are being widely criticized because the lack of transparency in their rating procedures and the huge impact of the ratings they disclose. However they are still the best available solution to provide financial markets with the information that their clients base their decisions on (see(Len-Soriano and Muoz-Torres, 2012)).

at their disposal. As such, credit risk models which make use of the clients' historical financial information are fairly useful. Generally, measuring credit risk follows three major steps:

- First: Modeling and measuring credit risk of individual/corporate clients;
- Second: Analysis of credit risk at a portfolio level;
- Third: Risk return analysis of the portfolio.

However, each aforementioned step includes sub-steps, for example, credit risk modelling process of individuals and corporations consist firstly of, defining the effective factors for credit risk, secondly, modelling and calculating the obligator's default probability (Bessis (2002)), setting the exposures limits, appropriate risk based pricing and finally, calculating the loss given defaults and ensuring there is appropriate loan loss provisioning. Similarly, analysis of credit risk at a portfolio level includes calculation of correlation or dependencies between obligors (see Rosenow et al. (2006)), secondly, the calculation of concentration risk and finally, the allocation of appropriate capital for expected or un-expected losses.

In this piece of study, the primary focus is on the first step, which is to calculate the credit risk of borrowers, although the definition of borrower is broad. If one is to examine from perspective of commercial, investment and retail banking, the term borrower refers to individuals and corporate entities. However, from the point of view of multilateral development banks (MDBs), the term borrower can have a much wider definition to include other financial institutions[4] besides individual and corporate credit customers. This is where selecting sound financial institutions and corporate customers is necessary for MDBs.

Taking into account the facts noted above, this study attempts to build two separate, simple and quantified credit scoring/rating models. One model to calculate the credit risk of financial institutions,

[4]Act as financial intermediary to distribute the MDB's funds to final beneficiaries which could include retail individuals or corporate customers. Therefore, in this case, MDBs only accept the risk of the financial institution and not from the final beneficiaries.

while the other to calculate credit risk of very large corporations who are the primary borrowers of MDBs. It is worth noting that different credit risk models exist for individuals and for corporations whose financial information and default history is available. However, there appears to be no such model to calculate the default risk of FIs and corporations, except for the models being used by international rating agencies.

As generally known, risk management can be considered as being a combination of art and intelligence. This entirely depends upon the risk modeller's art and intelligence, hence,, different limitations and criticism exist for designed models. However, what is of importance is that a risk modeller requires a set of assumptions. This enables the modeller to simplify the situation and build a model based on those assumptions. This is to provide clarification; it would not be possible to cover every aspects of credit risk within the framework set for a doctoral dissertation. This study builds the two credit scoring/rating models by examining the following:

1. Determining the main factors affecting financial performance of financial institutions;

2. Determining the main factors affecting financial performance of corporate entities,

3. Employing the defined determinant factors to setup two separate fuzzy logic based credit scoring/rating models

These topics form the backbone of the study and are investigated in essay style within the following three chapters. The three "core" chapters are self-contained and attempt to shed light on relevant issues and financial debates. In addition, the chapters intend to explore different aspects of the topic in an original way, by using a various methodologies. It goes without saying that the investigation into each of these matters merits further analysis on its own, and this study will therefore point out potential extensions in the concluding remarks within Chapter 5.

THE ECONOMIC COOPERATION ORGANIZATION TRADE AND DEVELOPMENT BANK

BALANCE SHEET AT 31 DECEMBER 2012
(Amounts expressed in thousands of ECO Unit ("EU") unless otherwise indicated.)

	Notes	31 December 2012	31 December 2011
ASSETS			
Loans and advances to banks	7	356,254	376,161
Loans and advances to customers	8	89,932	66,496
Investment securities: Available-for-sale	9	1,729	-
Derivative financial instruments	6	97	425
Intangible assets	10	144	198
Property and equipment	11	91	100
Other assets	12	156	191
Total assets		**448,403**	**443,571**
LIABILITIES			
Deposits from banks	13	123,706	126,839
Derivative financial instruments	6	2,096	954
Retirement benefit obligations	14	1,067	944
Other liabilities	15	813	905
Total liabilities		**127,682**	**129,642**
EQUITY			
Share capital	16	300,000	300,000
Revaluation reserve			
- Reserve for available-for-sale investment securities		2	-
Other reserves		13,929	10,199
Retained earnings		6,790	3,730
Total equity		**320,721**	**313,929**
Total liabilities and equity		**448,403**	**443,571**

Table 1.1: Typical MDB's Balance sheet

1.2 Overall theme and contribution

Lately, it appears that issues relating to credit risk measurement have received increased attention. Some of these issues have been addressed in three self-contained chapters. While the essays can be read independently, they are centred around and focus on a common concept. When considered together, all core chapters attempt to analyse and improve the deficiencies that exist in risk management. Therefore, it appears likely that further research will be spurred.

On the most general level, and as an important contribution with relation to contents and topics, the theme that re-occurs throughout the core chapters is to determine the main factors of performance for primary MDB's borrowers which are financial institutions and corporate entities. This is done so in order to later develop credit scoring/rating models. On the other hand, the entire focus of this thesis is to measure the risk of lending to financial institutions and corporate entities. These are main borrowers of trade and development banks, in terms of their credit portfolios. In the Table 1.1 it is shown how a MDB's credit portfolio resembles. As seen, the bulk of the asset size comprises of loans to FIs and corporations. Moreover, similar tables are also available for other MDBs and contained in Appendix A.1. The credit proposals expected scoring/rating results may be used later to select the best cases to lend to, followed by risk based price setting and ensuring that there is adequate loan loss provisions following disbursements. Figure 1.1 illustrates the emphasis of each core chapter, as part of the overall theme of this study.

Determining the above mentioned elements are segregated in two chapters, Chapter 2 for determining the performance factors of FIs using three-dimensional panel data and Chapter 3 for determining the performance factors of corporate entities using two-dimensional panel data. Generally, non-parametrical scoring techniques employ expert judgments in order to determine credit risk value drivers and the influences they have on credit scoring/rating. However, with the assistance of regression analysis, this dissertation determines factors and their significance/influence in Chapter 2 and 3. In Chapter 4, two separate scoring/rating models employing estimated coefficients are designed and discussed. Ultimately, information provided during the course of this study may prove to be beneficial in practice and in several aspects.

- In the context of early warning of deterioration of financial

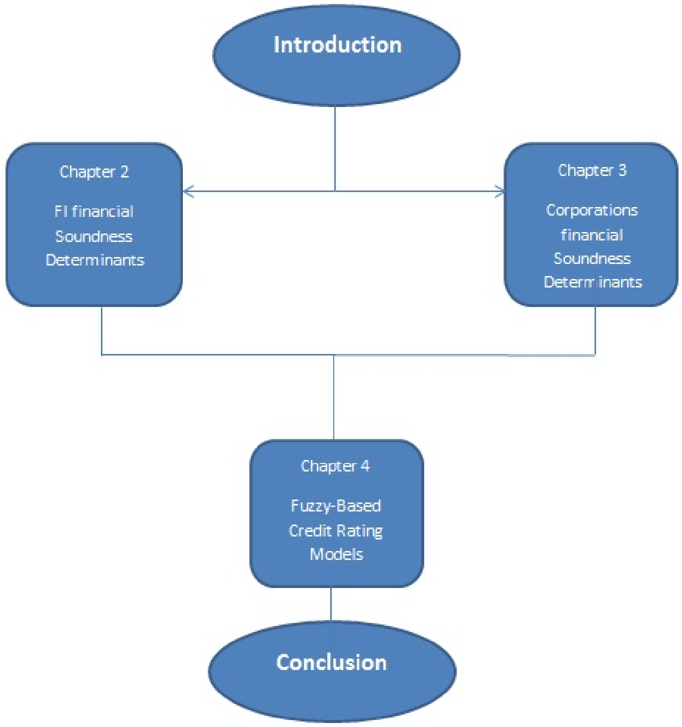

Figure 1.1: Thesis structure

health of a firm or a financial institution.

- From a perspective of credit risk assessment by any financial institution or organisation.
- In designing more complete and complex credit scoring/rating models for companies and financial institutions.
- For risk price setting, limit setting and loan loss provisioning of such loans.

1.3 Research questions, motivation and thesis structure

This introductory chapter is followed by the main analysis, in the form of the three self-contained core chapters. Since all core chapters are independent and possess their own distinct institutional background, extensive background information has been provided as part of the individual pieces of work. In this section the main motivation as well as the research questions are raised. The monograph is structured as follows:

Chapter 2 is very much set in the tone towards determining performance indicators of financial institutions. As mentioned previously, MDBs usually select several "sound" FIs to act as intermediaries. Therefore, selection of sound and healthy FIs is one of the main concerns of MDBs. Not all the FIs in different countries are rated by rating agencies, hence there appears to be a need for an in-house tailor made scoring model for FIs. Therefore, by employing a wide set of data in this capacity, in terms of the number of FIs in a number of Asian countries, for the period covered, by employing three-dimension regression analysis by testing numerous FI's specifics and macroeconomic variables, one could determine the main financial performance indicators.

Chapter 3 turns to focus on the main drivers of financial performance for corporate entities. As known, MDBs, as a general rule prefer to work with large corporate customers. Selection of "healthy" corporations for lending purposes, the timing of lending, appropriate risk based pricing even following disbursement, ensuring that adequate loan loss provisions exist to protect the equity of MDB's are other concerns. The data examined is similar to that in Chapter 2 in terms of the data set, however, the countries covered include European countries that have economies in transitions and have only recently started privatisation. Similarly, as followed in the second core chapter, by employing two-dimension regression analysis and by being able to test different macro and micro variables it was possible to determine the main financial performance factors of very large corporations.

Chapter 4 relates to the development of credit scoring/rating models to compare the credit risk of proposed credit customers. This chapter is followed by chapter 2 and chapter 3 where the main drivers of profitability for firms and financial institutions are determined. In this chapter, by employing a non-parametric fuzzy technique and by making use of results in previous chapters, two separate credit scoring/rating models for calculating the credit risk of FIs and large corporations is designed.

Chapter 5 finally, provides an overall conclusion of the thesis, summarising and highlighting policy implications, as well as providing directions for further research.

Chapter 2

Bank-Specific, Banking Industry-Specific and Macro-economic Determinants of Profitability: Evidence from Asian Countries

2.1 Introduction

Recently, the importance of monitoring the banking sector and of the financial health of FIs has emerged due to the frequent occurrences of banking credit crises, first with the Asian crises of 1990 and the more recent financial crises which upset the global market in 2008.

A sound and profitable financial sector is better able to withstand negative shocks and contribute towards the stability of the financial system. Therefore, the determinants of FIs performance have attracted much interest from academic researchers, as well as of the bank management, financial markets and supervisory authorities.

Furthermore, based on recent historical data, the number of failures in banking sector has increased when compared to the period before 1980. Therefore, the requirement for a more effective system of monitoring FIs has become vital. Moreover, as stated by Barr et al. (1999) "Banking regulators are particularly interested in advanced and improved failure prediction models for several reasons. First is the belief that failure can be avoided or the bailout costs can be minimized through an early detection of an institution's troubled status and intervention by regulatory authorities. An accurate and timely identification of a bank's potential for failure would also assist in targeting of inspection and allow for a more effective allocation of resources for on-site supervision. Finally, while the off-site supervision could never replace on-site examinations, it can complement the on-site process by identifying troubled institutions that need early examination or possible intervention." Off-site surveillance provides a dynamic representation of the financial situation of banks. Using FIs financial information, enables supervisors to schedule and plan exams efficiently. Off-site surveillance also provides banks with incentives to remain financially sound between on-site visits (Yuen and Ling, 2006).

Since the profitability of banks is the most important indicator of financial health and credit worthiness, it is utilised for assessing the financial stability of banks. A decrease in profitability and subsequent incurrence of loss are the major factors which lead to the depletion of capital of FIs.

Most studies relating to bank profitability make use of linear models to identify the impact of the various factors which are important in explaining profitability. Although these studies show that it is possible to undertake a useful analysis of bank profitability, some issues are not addressed and dealt with in detail. First, the relevant literature principally considers determinants of profitability at the bank and/or industry level while there appears to be a lack of investigation of the effect on the macroeconomic environment[1]. Secondly, existing literature employs a short time dimension of the panels for estimation. However, if data includes several episodes of crises, the result may be more accurate. Third, most studies have been undertaken for a single country's financial institutions which does not permit one to apply

[1]The more accurate and realistic analysis of FIs is conditional to the considerations at the macro-economic, social, as well as the political environment of the country (as exogenous factors on banks profitability), because the macroeconomic environment affects the financial market of that country.

and generalise results for other countries.

Therefore, in order to fill the existing gap in existing literature, this paper investigates by means of a two-way panel[2] regression model framework, the effect of bank-specific, industry-specific and macro-economic determinants on the profitability of banks. Bank-specific determinants of profitability include and can be grouped into efficiency, liquidity, credit risk, leverage and sensitivity to the market. The second group of determinants describes industry-structure factors which affect the profitability of banks. The latter are not created as a direct result of managerial decisions e.g. banking sector borrowing rate. The third group of determinants relates profitability to the macro-economic environment within which the banking system operates e.g. GDP growth rate and inflation rate. In addition, the current study represents one of the few attempts to identify the relationship between the exchange rate regime and bank profitability (see Aburime (2008)). Moreover, in order to describe the group variation (countries and FIs) dummy variables have been included to account for and represent the developmental status of countries (developed, developing) in the models.

This study selects a sample comprising of several Asian countries that are borrowing members of the Asian Development Bank (one of the Multilateral Development Bank[3], refer to the balance sheet in Table A.2). The sample covers the period between 1990 to 2010 and encompasses several episodes of financial crises i.e. the Asian financial crises and the recent global financial crises.

The empirical results suggest that bank specific determinants affect bank profitability significantly, in line with prior expectations. The evidence indicates that the impact of inflation is asymmetrical

[2]Firstly, it tests for any variation between countries and FIs in terms of ROA and then models the variation by adding independent variables.

[3]Multilateral Development Banks are financial institutions that provides financing for national development. These types of banks are formed by a group of countries, consisting of both donor and borrowing nations. They finance developmental projects, provide working capital for corporate entities and finance financial institutions which act as their intermediaries in member countries. Therefore, like central banks, their knowledge on matters relating to the financial health of financial institutions are vital for their credit portfolio management.

and industry variables are found to have substantial effects on bank profitability.

The study is divided into seven sections. Section 2 presents the literature review. Section 3 presents theory of profitability determinants of banks. Section 4 and 5 describe methodology and data. Section 6 and 7 comprise of regression results and concluding remarks.

2.2 Literature review

Within literature, bank profitability is typically measured by the return on assets (ROA) or the return on equity (ROE). It is normally expressed as a function of endogenous and exogenous determinants. Endogenous determinants are usually defined as variables that are primarily influenced by management decisions and policy targets of banks. Such profitability determinants often include the level of liquidity, asset quality or provisioning policy, capital adequacy, cost management and bank size. On the other hand, the exogenous determinants, both industry and macro-economic related variables reflect the economic and legal environment where the credit institutions operate.

Changes in credit risk of individual or corporate customers may influence the financial health of the FIs's loan portfolio - which in turn, could affect the performance of such financial institutions. This is due to the fact that lending constitutes the bulk of FIs assets and involves greater risk when compared to other bank assets such as government securities. As reported by Athanasoglou et al. (2006), one can chose the non-performing loans and loan loss provisions as proxies for credit risk or asset quality. In addition, amongst other findings, the study above found a negative impact of loan loss provisions to loans ratio and of the profitability of the banks. It concluded that variations in bank profitability are largely attributable to variations in credit risk, since increased exposure to credit risk is normally associated with decreased firm profitability. They employed allowance for doubtful debt over total loan ratio as index for the credit quality. Other researchers such as Fadzlan (2011), Vong and Chan (2008) and Khizer et al. (2011), have all made use of the same ratio as proxy for asset quality or credit risk index. Their results indicate negative impacts of asset quality indexes on profitability. Moreover, in research undertaken at Reserve Bank of Australia, Marianne (2001) defines impaired assets to total assets ratio as credit risk factor or asset quality index and the results of their work also demonstrate a negative impact of credit quality indexes on the profitability of banks.

Another factor that affects profitability is leverage (overall capitalisation). This factor has demonstrated to be an important in explaining the performance of financial institutions; however, its impact on bank profitability is ambiguous. Higher levels of equity could reduce the cost of capital, leading to a positive impact on profitability. Moreover, an increase in capital may raise expected earnings by reducing the expected costs of financial distress, which includes bankruptcy. Indeed, most studies that make use of capital ratios as an explanatory variables of bank profitability observe a positive relationship. Finally, Athanasoglou et al. (2006), Valentina and McDonald (2009), Vong and Chan (2008), Demirguc-Kunt and Huizinga (2000) and Naceur (2003) all suggest that capital is better modelled as an endogenous determinant of bank profitability, as higher profits may lead to an increase in capital and they have been able to employ equity to total assets ratio as an index for leverage.

The efficiency factor is another determinant of profitability, which is substituted by non-interest income or operating expenses to total assets ratio. For the most part, the literature argues that reduced expenses improve efficiency and raise the profitability of a FI, implying a negative relationship between an operating expenses ratio and profitability (Athanasoglou et al., 2006). However, other studies undertaken by Indranarian (2009), Naceur (2003), Demirguc-Kunt and Huizinga (2000) and Vong and Chan (2008) suggest a positive relationship, implying that high profits earned by firms may be appropriated in the form of higher payroll expenditures paid on more productive human capital.

The size of FIs is generally used to capture potential economies or dis-economies of scale in the banking sector. This factor is usually expressed as a log of assets or bank loans to the country's domestic credit ratio as employed by Valentina and McDonald (2009), Marianne (2001), Naceur (2003), Athanasoglou et al. (2006), Khizer et al. (2011) Fadzlan (2011) and Indranarian (2009).

If significant economies of scale exist, the size of banks can have a positive impact on the profitability of banks. Some researchers also suggest that the effect of growing the bank's size on profitability may be positive only up to a certain limit. Beyond this point the effect of size could be negative due to bureaucracy and other reasons. Hence, the size-profitability relationship can be expected to behave in a non-linear manner.

Regarding the factors related to banking industry, one is able to employ banking system reform, concentration (with expectation of ambiguous impact) (Athanasoglou et al., 2006), banking industry interest rate (with expectation of positive impact) and banking industry non-performing loans (with expectation of negative impact).

In relation to other set of variables such as macro-economic factors and their impact on the profitability of banks, one can expect to see a positive effect of GDP growth on profitability since economic growth encourages banks to lend more and in turn, permitting them to charge higher margins, as well as improving the quality of their assets. Indranarian (2009), Naceur (2003), Marianne (2001) and Vong and Chan (2008) have made use of per capita income as proxy for growth and suggest that this variable exerts a strong positive effect on bank earnings. Demirguc-Kunt and Huizinga (2000) attempts to identify possible cyclical movements in bank profitability and the extent to which bank profits are correlated with the business cycle. Their findings suggest that such correlation exists, although the variables used were not direct measures of the business cycle.

Another widely used proxy for capturing and understanding the effects of the macro-economic environment on bank profitability is inflation. Athanasoglou et al. (2006) notes that the effect of inflation depends on whether wages of banks and other operating expenses increase at a faster rate than inflation. The relation between inflation and profitability hinges upon the degree of maturity that an economy exhibits so that future inflation can be accurately forecasted. Thus, the bank can manage their operating costs, accordingly. As such, the relationship between the inflation rate and profitability is ambiguous and depends whether or not inflation is anticipated. An inflation rate fully anticipated by the bank's management implies that banks can adjust interest rates appropriately, in order to increase their revenues quicker than their costs and thus achieve higher profits. On the contrary, unanticipated inflation could lead to improper adjustment of interest rates and hence of the possibility that costs could increase faster when compared to revenues (see Vong and Chan (2008)). However, most studies observe a positive relationship between inflation and bank performance (see (Athanasoglou et al., 2006)).

In terms of methodology, data frequency and data sets the literature can be divided into two groups, the first including studies that have been undertaken for single countries such as studies on Greek banks, (Athanasoglou et al., 2006), Nigerian Banks (Aburime, 2008), Taiwanese banks (Indranarian, 2009), Macao banks (Vong and Chan, 2008), Australian banks (Marianne, 2001), Tunisian banks (Naceur, 2003) Korean banks (Fadzlan, 2011) and Pakistani Banks (Khizer et al., 2011). All these studies have employed one way panel data (observations are stacked by time, not by banks) for just a single country and primarily for short periods of time. The second group of studies has made use of data belonging to more than one country. For this group, it may be refereed to the research undertaken for 44 countries by Demirguc-Kunt and Huizinga (2000) and another study undertaken for Sub-Saharan African countries (Valentina and McDonald, 2009). Demirguc-Kunt and Huizinga (2000) have averaged the financial data of banks over time and have come up with the one way panel data structure (observation are stacked by banks, not by countries).

Both sets of studies have only made use of one way panel data format and none of the studies have considered the unobserved countries effects. In this regards, this study is unique since it makes use of two-way panel data structure or three-dimensional panel data. Data for 18 Asian countries, spanning over a period of 20 years has been utilised in an attempt to contribute to the literature.

2.3 Bank profitability

In this section, variables that are used to measure profitability are listed and explained, Secondly, the determinants of bank profitability, which have been grouped into three groups: banks-specific, industry-specific and macro-economic factors, are explained.[4]. See Figure 2.1.

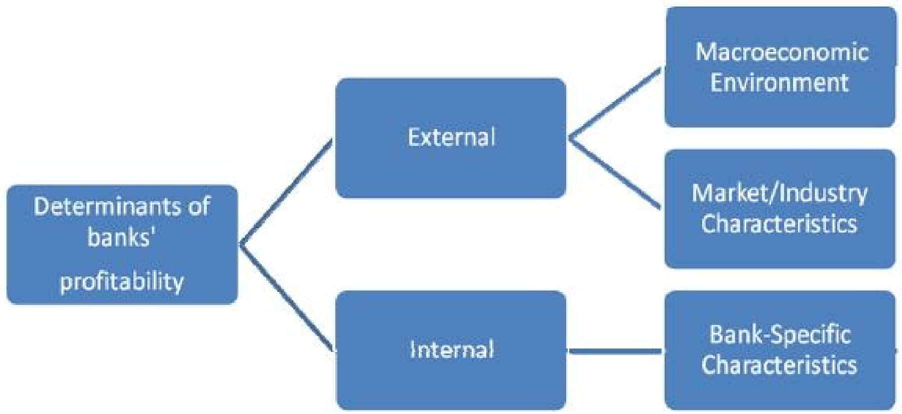

Figure 2.1: Determinants of banks'profitability
Indranarian (2009)

2.3.1 Measure of profitability

As mentioned in the literature review, return on equity (ROE) and return on assets (ROA) can be used as an index for measuring the profitability of banks. The first ratio measures the rate of return on ownership interest (shareholder's equity) of common stock owners. It measures a firm's efficiency in relation to generate profits from every unit of the equity of shareholders (also referred to net assets or assets minus liabilities). Alternatively, in other terms - the term ROE is an indicator of how well a company is able to use investment funds in order to generate growth in earnings. The second ratio (ROA) is an indicator to show what a company can do with its resources, i.e. how many dollars of earnings is derived per dollar of assets controlled. It is a useful measure for comparing competing companies in the same industry and the value will vary widely across different industries. Return on assets provides an indication of the capital intensity of a

[4]see Indranarian (2009) for using a similar approach

company, which will depend on the industry; companies which require large initial investments will generally have lower return on assets.

2.3.2 Bank-specific determinants

For bank-specific determinants reliance is placed in some of the components included in CAMEL(S)[5] (see Appendix A.2) methodology. The components included are capital protection, asset quality, management competence, efficiency, liquidity and sensitivity to the market. Individual components and their relationship with profitability are described in detail below.

1-Capital Protection Structure and Leverage. Adequacy of capital is one of the important elements for assessing the financial status of FIs. A financial institution is expected to maintain capital that is commensurate with the nature and extent of risk it is exposure to. The effect of credit, market, and other risks influencing the institution's financial condition should be taken into consideration, when evaluating the adequacy of capital. The type and quantity of risk inherent in an institution's activities will determine the extent to which it may be necessary to maintain capital at levels above required regulatory minimums. This required regulatory minimums are essentially defined by Basel II regulations to appropriately reflect potentially adverse consequences that these risks may have on the institution's capital (Yuen and Ling, 2006). The capital adequacy of an institution is assessed by evaluating the ability of FIs to raise capital from markets and other sources, including support provided by a parent holding company. Capital protection is primarily captured by the following two ratios: one, by capital adequacy ratio (CAR) and secondly, by equity to asset ratio, both of which are expected to have a positive impact since the greater the capital is, the FI needs to pay a lesser amount for interest expenses of its financial borrowing.

Financial leverage ratios provide an indication of the long-term solvency of the firm. These ratios measure the extent to which the firm is using long term debt. In order to select a proxy of leverage,

[5]Other standard factors such as CAMELS are PATROL, ORAP, GIRAFE, PEARLS but CAMELS is more popular.

debt ratio which is defined as total debt divided by total assets and the debt-to-equity ratio, which is defined as total debt divided by total equity, can be employed.

2-Asset Quality. The asset quality reflects the quantity of existing and potential credit risk associated with the loan, investment portfolios and off-balance sheet transactions. The ability of management to identify, measure, monitor, and control credit risk is also reflected in asset quality. During the evaluation of asset quality, one should consider the adequacy of allowance for loan losses and exposure to counterparties. Some popular asset quality ratios include loan loss provision/total loans ratio, net charge offs/average total loans ratio, actual loan losses/provisions ratio, loan loss reserves/non-performing assets ratio and non-performing assets/total assets ratio. It is expected that asset quality ratios, mentioned above, have a negative impact on profitability.

3-Earning Strength or Efficiency Ratio. Not only does this component reflect the quantity and trend of earnings, but also factors that may affect the attainability or quality of earnings. The quantity, as well as the quality of earnings, can be affected by excessive or inadequately managed credit risk. This can result in loan losses, which may require additions to the allowance for loan and lease losses. Earning performance ratios determine if the operations of banks generate adequate returns on the assets and equity. The gross profit margin is a measure of the gross profit earned on sales. Some of the popular ratios for profitability monitoring are; return on loans, return on investment, interest margin, net income per staff and net income to staff costs ratios. It is expected that earning has a positive impact on profitability.

4-Liquidity. While evaluating the adequacy of liquidity position of FIs, consideration should be given to the current level and prospective sources of liquidity compared to funding needs, as well as to the adequacy of funds, management practices relative to the institution's size, complexity, and risk profile. In general, management practices for funds should ensure that an institution is able to maintain a certain level of liquidity which is sufficient to meet its financial obligations in a timely manner and to fulfil legitimate banking needs of its community. Practices should reflect the ability of the institution to manage unplanned changes in funding sources, as well as be able to react to changes in market conditions that affect the ability to liquidate assets with minimal loss quickly. In addition, fund management practices should ensure that liquidity is not maintained at a high cost, or through undue reliance on funding sources that may not be available in times of financial stress or due to adverse changes in market conditions (Yuen and Ling, 2006). It is expected that the impact of liquidity on profitability is ambiguous. Some of the liquidity ratios used in the literature include deposit to asset ratio, total loan to total deposits ratio and total loans to total assets ratio (Athanasoglou et al., 2006).

5-Market Risk (Sensitivity to Market). The sensitivity to market risk component reflects the degree to which changes in interest rates, foreign exchange rates, commodity prices, or equity prices can adversely affect FIs' earnings. When evaluating this component, consideration should be given to management's ability to identify, measure, monitor, and control market risk. Also, consideration ought to be given to the adequacy of the FIs capital and earnings, in relation to its level of market risk exposure (Yuen and Ling, 2006). The ratio of price to book value per share can also be used as proxy for measuring sensitivity towards the market. This ratio is a financial ratio used to compare a company's book value with respect to its current market price. Book value is an accounting term denoting the percentage of the company that is held by shareholders, in other words, the company's total tangible assets excluding its total liabilities. This ratio is expected to have a positive effect on profitability of FIs. As reported by Athanasoglou et al. (2006) "In 1999, total profits, and particularly those resulting from financial transactions, exhibited a significant increase (more than 100%), mainly due to the boom in share prices in the Athens Stock Exchange." Another reason appears to be that usually the management has a monetary interest in the company i.e. they either possess a significant number of company shares, have salary incentives or stock options linked to performances, which is tied to the company's stock prices.

It can be seen that the bank-specific determinants described above are useful indicators for measuring the financial performance of FIs. The majority of these ratios can be calculated using information from financial statements. Moreover, financial ratios, unlike absolute figures, can be used to compare the financial health of FIs.

2.3.3 Industry and macro-economic determinants

Beside bank-specific factors, which primarily relate to internal decision making processes, exogenous factors are related to the banking industry and the macro-economic environment of the country and have an impact on the profitability of banks. Some of the possible industry factors include domestic credit provided by the banking sector(as a percentage of GDP), deposit interest rates, lending interest rates, interest rate spread, bank capital to total assets ratio, non-performing loans to total gross loans ratio, bank liquidity reserves to bank assets ratio and claims on central government. Moreover, for macro-economic determinants on the profitability of banks, one may refer to GDP per capita growth, real interest rates, current account balance, inflation rates (CPI/GDP deflator), money and quasi money supply (M2), gross domestic saving (as a percentage of GDP), trade (as a percentage of GDP), foreign direct investment net inflow (as a percentage of GDP) and financing via the international capital market (gross inflow as a percentage of GDP).

It would be expected that per capita GDP will have a positive effect on the profitability of FIs since growth in per capita GDP implies an expansion of the economy, which in turn implies there is more activity for banking operation. Consequently, there is increased profitability (Athanasoglou et al., 2006). Cyclical output and the level of economic development are usually used to represent business cycles since the profits of banks are expected to be correlated with business cycles - profits being higher in case of upswings and lower in case of downswings (see (Huizinga and Demirg-Kunt, 1999)).

An ambiguous effect on profitability can be expected in respect to inflation. In cases where FIs have the ability to adjust their margins with the inflation rate, profitability behaves in a pro-cyclically manner with inflation. On the other hand, in cases where FIs are unable to adjust their margins with the inflation rate, profitability behaves in counter-cyclically manner with inflation rate (Vong and Chan, 2008).

Money and quasi money (M2), an index for expansionary monetary policy is expected to have a positive impact on profitability. Since banks are flushed with more money as consequence of expansionary monetary policies, they lend more.

Deposit and lending rates as indexes for industry related variable are expected to have negative and positive impacts on the profitability of the entire banking system.

In addition to the above mentioned bank-specific and industry specific factors and their impact on profitability, one may wish to make use of dummy variables in order to capture and analyse the effects of developmental status and the type of exchange rate regime, on FIs profitability (see (Marianne, 2001)).

2.4 Methodology

In this section, the methodology employed for identifying the determinants affecting the profitability of banks is explained. The section comprises of two sub-sections. First, one-way and two-way panel models are described. Secondly, the variance component model and mixed model that will be employed in this study are explained.

2.4.1 One way versus two way error component model

For usual panel data structure, observations are stacked by time, for instance, for panel model with m cross sectional units over n time periods will have:

$$\mathbf{y}_{it} = \boldsymbol{\alpha}_i + \mathbf{x}_{2it}\boldsymbol{\beta}_2 + \mathbf{x}_{3it}\boldsymbol{\beta}_3 + ... + \mathbf{x}_{kit}\boldsymbol{\beta}_k + \mathbf{u}_{it} \tag{2.1}$$

or

$$\mathbf{y}_{it} = \boldsymbol{\alpha}_i + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \mathbf{u}_{it} \tag{2.2}$$

when $\boldsymbol{\alpha}_i$ is fixed, it yields the ***fixed effect model***. However if $\boldsymbol{\alpha}_i$ is assumed to be random in cross-sections, $\boldsymbol{\alpha}_i$ will be:

$$\boldsymbol{\alpha}_i = \boldsymbol{\alpha} + \boldsymbol{\delta}_i \tag{2.3}$$

where $\boldsymbol{\alpha}$ is the mean intercept and $\boldsymbol{\delta}_i$ is individual cross sectional effect which is randomly distributed. Thus, it can be written;

$$\mathbf{y}_{it} = \boldsymbol{\alpha} + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \boldsymbol{\delta}_i + \mathbf{u}_{it} \qquad i = 1, 2, ..., m, \quad t = 1, 2, ..., n \tag{2.4}$$

The above model is known as ***one-way random effect*** or ***one-way error component*** model. Instead of just cross-sectional effect one might also like to capture the time effect. Thus, it can be written;

$$\boldsymbol{\alpha}_{it} = \boldsymbol{\alpha} + \boldsymbol{\delta}_i + \boldsymbol{\lambda}_t \tag{2.5}$$

where $\boldsymbol{\alpha}$ is the overall effect, $\boldsymbol{\delta}_i$ is individual cross sectional effect, and λ_t is the time effect, so for this case, the model becomes:

$$\mathbf{y}_{it} = \boldsymbol{\alpha} + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \boldsymbol{\delta}_i + \boldsymbol{\lambda}_t + \mathbf{u}_{it} \quad i = 1, 2, ..., m, \;\; t = 1, 2, ..., n \tag{2.6}$$

when $\boldsymbol{\delta}_i$ and $\boldsymbol{\lambda}_t$ are fixed, the above model is called ***two-way fixed effect*** model. However, when $\boldsymbol{\delta}_i$ and $\boldsymbol{\lambda}_t$ are random, the model is called a ***two-way error component model***, or ***two-way random effect model***.

2.4.2 Model

Since the data structure is clustered, possessing three levels which include FI, time and country, first, a group variation check is undertaken. This can be accomplished by using the variance component model (random intercept model). If it is found that there is significant group variation, it means that the groups have different intercepts from the mean regression line. In addition, related explanatory variables for each level (financial variables, as well as macro-economic variables) are added and verified for fixed and random effects.

Variance components/random intercept model

In order to check group effects, a two-way random intercept model or variance component model is used, as presented below. This model does not appear to be interesting by itself; however, it provides a baseline which enables comparison of more complex models (with more descriptive variables).

$$\Pi_{itk} = \beta_{0itk} Cons \tag{2.7}$$

$$\beta_{0itk} = \beta_0 + \nu_{0k} + u_{0tk} + e_{0itk} \tag{2.8}$$

$$\left[\ \nu_{0k}\ \right] \sim N(0, \Omega_\nu) : \Omega_\nu = \left[\ \sigma^2_{\nu 0}\ \right]$$

$$\left[\ u_{0tk}\ \right] \sim N(0, \Omega_u) : \Omega_u = \left[\ \sigma^2_{u0}\ \right]$$

$$\left[\ e_{0itk}\ \right] \sim N(0, \Omega_e) : \Omega_e = \left[\ \sigma^2_{e0}\ \right]$$

Where Π_{itk} is the dependent variable, $Cons$ is constant, ν_{0k} is the random effect at country level, u_{0tk} is the random effect at time level, and e_{0itk} is the random effect at FI level. Ω_ν is the variance between countries, Ω_u is variance between times within countries and Ω_e is variance between FIs within times and within countries and β_0 is the population mean. To test the significance of coefficients and random intercepts t-test[6] can be employed .

[6]This study has made use of a specific software, MLWIN (See Steele and Rasbash (2009)) which is specialised for fitting multilevel models with more than two level (one way panel) and the required data structure for this software is in long data format. By using this software, it is possible to test for random as well as fixed effect models.

Mixed model/two-way random intercept and random slope model

Conceptually, if data has a hierarchical structure using more than one-way panel model, as stated by Steele and Rasbash (2009) it "enables the researcher to understand where and how effects are occurring. It provides better estimates in answer to the simple questions for which single-level analysis were once used and in addition allows more complex questions to be addressed". Furthermore, ignoring clustering generally causes standard errors of regression coefficients to be underestimated[7] leading to the test of significance and confidence intervals to be biased. This can lead to unreliable results (for more detail in this issue refer to Chen (2012) where they conclude that when a higher level structure in cross-sectional data is ignored, the variance at the higher level is redistributed to the lower level, thus affecting the hit rate and group mean and standard error estimates.).

To test the relationship between bank profitability and the bank-specific, industry related and macro-economic determinants described above, a two-way panel model or three-level model is estimated. It is structured with FIs at the first level, time (t) at the second level and countries (k) at the third level. Therefore, the three-level or two-way random effect model can be specified as below:

$$\Pi_{itk} = \beta_{0itk} Cons + \sum_{j=1}^{J} \beta_j X_{itk}^{j} + \sum_{l=1}^{L} \beta_l X_{tk}^{l} + \sum_{m=1}^{M} \beta_m X_{tk}^{m} + \sum_{n=1}^{N} \beta_n X_{k}^{n} \tag{2.9}$$

[7] As an example, consider models of electoral behaviour. Voters are clustered within wards and wards within constituencies. If standard errors were underestimated, it might be inferred, for example, that a real preference for one party existed or course of action over another, when in fact that preference, estimated from the sample, could be ascribed to chance. Correct standard errors would be estimated only if variation at the ward and constituency level were allowed in the analysis. Employing more than one-way panel model provides an efficient way of undertaking this task. Also, it makes it possible to model and investigate the relative sizes and effects of ward characteristics and of constituency characteristics on electoral behaviour, as well as that of individual characteristics such as social group (Steele and Rasbash, 2009).

$$\beta_{0itk} = \beta_0 + \nu_{0k} + u_{0tk} + e_{0itk} \tag{2.10}$$

$$\beta_{1itk} = \beta_1 + \nu_{1k} + u_{1tk} + e_{1itk} \tag{2.11}$$

.

$$\beta_{(s1)itk} = \beta_0 + \nu_{(s1)k} + u_{(s1)tk} + e_{(s1)itk} \tag{2.12}$$

$$\begin{bmatrix} \nu_{0k} \\ \nu_{1k} \\ \nu_{2k} \\ \nu_{3k} \\ . \\ \nu_{(s1)k} \end{bmatrix} \sim N(0, \Omega_\nu) : \Omega_\nu = \begin{bmatrix} \sigma^2_{\nu 0} & & & & & \\ \sigma_{\nu 01} & \sigma^2_{\nu 1} & & & & \\ \sigma_{\nu 02} & \sigma_{\nu 12} & \sigma^2_{\nu 2} & & & \\ \sigma_{\nu 03} & \sigma_{\nu 13} & \sigma_{\nu 23} & \sigma^2_{\nu 3} & & \\ . & . & . & . & . & \\ \sigma_{\nu 0(s1)} & \sigma_{\nu 1(s1)} & \sigma_{\nu 2(s1)} & \sigma^2_{\nu 3(s1)} & . & \sigma^2_{\nu(s1)} \end{bmatrix}$$

$$\begin{bmatrix} u_{0tk} \\ u_{1tk} \\ u_{2tk} \\ u_{3tk} \\ . \\ u_{(s1)tk} \end{bmatrix} \sim N(0, \Omega_u) : \Omega_u = \begin{bmatrix} \sigma^2_{u0} & & & & & \\ \sigma_{u01} & \sigma^2_{u1} & & & & \\ \sigma_{u02} & \sigma_{u12} & \sigma^2_{u2} & & & \\ \sigma_{u03} & \sigma_{u13} & \sigma_{u23} & \sigma^2_{u3} & & \\ . & . & . & . & . & \\ \sigma_{u0(s1)} & \sigma_{u1(s1)} & \sigma_{u2(s1)} & \sigma^2_{u3(s1)} & . & \sigma^2_{u(s1)} \end{bmatrix}$$

$$\begin{bmatrix} e_{0itk} \\ e_{1itk} \\ e_{2itk} \\ e_{3itk} \\ . \\ e_{(s1)itk} \end{bmatrix} \sim N(0, \Omega_e) : \Omega_e = \begin{bmatrix} \sigma^2_{e0} & & & & & \\ \sigma_{e01} & \sigma^2_{e1} & & & & \\ \sigma_{e02} & \sigma_{e12} & \sigma^2_{e2} & & & \\ \sigma_{e03} & \sigma_{e13} & \sigma_{e23} & \sigma^2_{e3} & & \\ . & . & . & . & . & \\ \sigma_{e0(s1)} & \sigma_{e1(s1)} & \sigma_{e2(s1)} & \sigma^2_{e(s1)} & . & \sigma^2_{e(s1)} \end{bmatrix}$$

where Π_{itk} is the profitability of the bank i at time t for country k, with $i = 1, , ..., N$; $t = 1, ..., T$ and $k = 1, ..., K$, $Cons$ is a constant term. $\sum_{j=1}^{J} \beta_j X_{itk}^j$ are the series of explanatory variables related to financial institutions, $\sum_{l=1}^{L} \beta_l X_{tk}^l$ are the series of industry, $\sum_{m=1}^{M} \beta_m X_{tk}^m$ are the series of macro-economic variables and $\sum_{n=1}^{N} \beta_n X_k^n$ are the country dummy variable, β_0 is the population mean, ν_{0k}, u_{0tk} and e_{0itk} are random intercept effects for countries, time and FIs as explained in variance component model and $\sigma_{\nu 0}^2$, σ_{u0}^2 and σ_{e0}^2 are their related variances. If one wants to model slope coefficients also as random, the diagonal and off diagonal elements of Ω_ν, Ω_u and Ω_e variance-covariance matrixes appears. $s1$ is the summation of j, l, m & n. The above model is a two-way error component or random effect regression model, where $\nu_{0tk} \sim N(0, \sigma^2)$ and $u_{0k} \sim N(0, \sigma^2)$ are independent from $e_{itk} \sim N(0, \sigma^2)$. Iterated general least squares (IRGLS) are made use of in order to estimate the model. The model is run until convergence is achieved.

2.5 Data

The main objective of this study is to identify the primary determinants of the profitability of banks. For this purpose, bank-specific, macro-economic and industry specific variables are employed. Few studies have been undertaken for Asian countries in terms of banking profitability determinants. Therefore this study selected data of FIs from 18 Asian countries[8] over the period between 1990 to 2010. These countries have been selected according to the availability of data in the Bloomberg data base. Table 2.1 lists the variables employed to proxy profitability and its determinants (also included are the expected effects of determinants according to the literature). As it can be observed from the table, some variables are expected to have positive effects on the profitability of banks e.g. net interest margin

[8]Armenia, China, Georgia, Hong Kong, Kazakhstan, Kyrgyz Republic, Malaysia, Philippine, Singapore, Sri Lanka, Thailand, Uzbekistan, Vietnam, India, Indonesia, Pakistan, Azerbaijan, South Korea, which are all borrowing members of Asian Development Bank.

(NIM)[9], annual GDP growth while other variables are expected to have negative impact on the profitability of banks e.g. loan to deposit ratio and deposit interest rate. In addition, some of the variables are expected to have an ambiguous effect on the profitability of banks e.g. annual inflation rate.

		Variable	Expected effect
	Dependent Variable	Return on Equity	
Determinants	Organizational Factors	Efficiency	
		Net Interest Margin	+/-
		Non-performing Asset/Total Asset	+
		Loan/Deposit	-
		Price/Book value per share	+
		Log of total aset (size of bank)	+
	Industry Factors	Deposit rate	+
	Macroeconomic Factors	GDP Growth	+
		Consumer Price Index (2005=100)	+
		Exchange rate regime:	
		Different type of currency peg	+/-
		Managed float regime	+/-
		Free float regime	+/-

Table 2.1: Variables and their expected signs

In Figure 2.2 and Figure 2.3 the distribution of the data sample is presented. In total, there are 2112 unbalanced[10] observation over a period of 21 years for 218 FIs. The majority of the observations (out of a total of 2112 observations) belong to India, Philippine, Indonesia, Malaysia, Thailand, Pakistan. The least number of data observations

[9]Net interest income is the difference between interest earned on loans and other assets and interest paid on funding. It excludes income from fees, commissions, trading activities and one-off gains classified as non-interest income in annual reports. The net interest margin is defined as the ratio of net interest income to average interest earning assets. It captures the profitability of a bank's core intermediation function.

[10]For some countries information for very few FIs and (or) for few years only was obtained. It is considered that even a single FI, can play the role of an effective entity in causing a major financial crash as Mannasoo (2004) stated "every single institution has a special value on small, transparent market. Even if the institution in question is not systemically important, its default would dismantle the reputation of the whole sector."

belong to Uzbekistan, Kyrgyz Republic, Armenia and Georgia. Due to the availability of data for recent years, the data distribution is skewed towards the right. The data set comprises of bank related financial data obtained from the financial statements of banks. The other type of data set comprises of macro-economic data obtained from World Bank macro-economic database.

The data used is structured as long format panel, where countries and banks are stacked by time which results in a three levels structure. By making use of such a format, it is possible to include the time variant variables[11] for countries (macro-economic and industry variables) as well as time variant variables for FIs.

[11] In contrast, time invariant variables which are fixed during the time exist e.g. exchange rate regime.

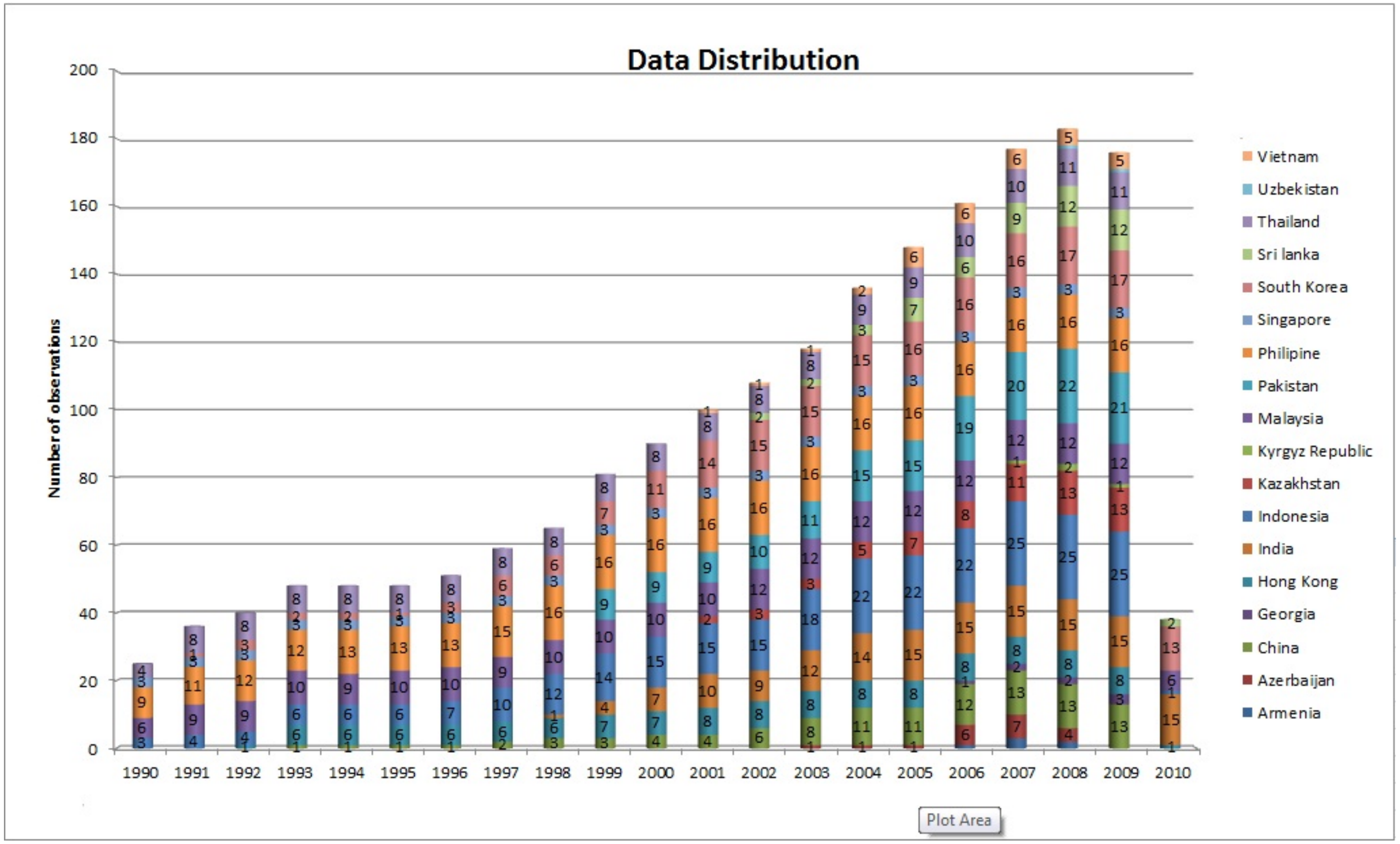

Figure 2.2: Data Distribution for Countries over the Years

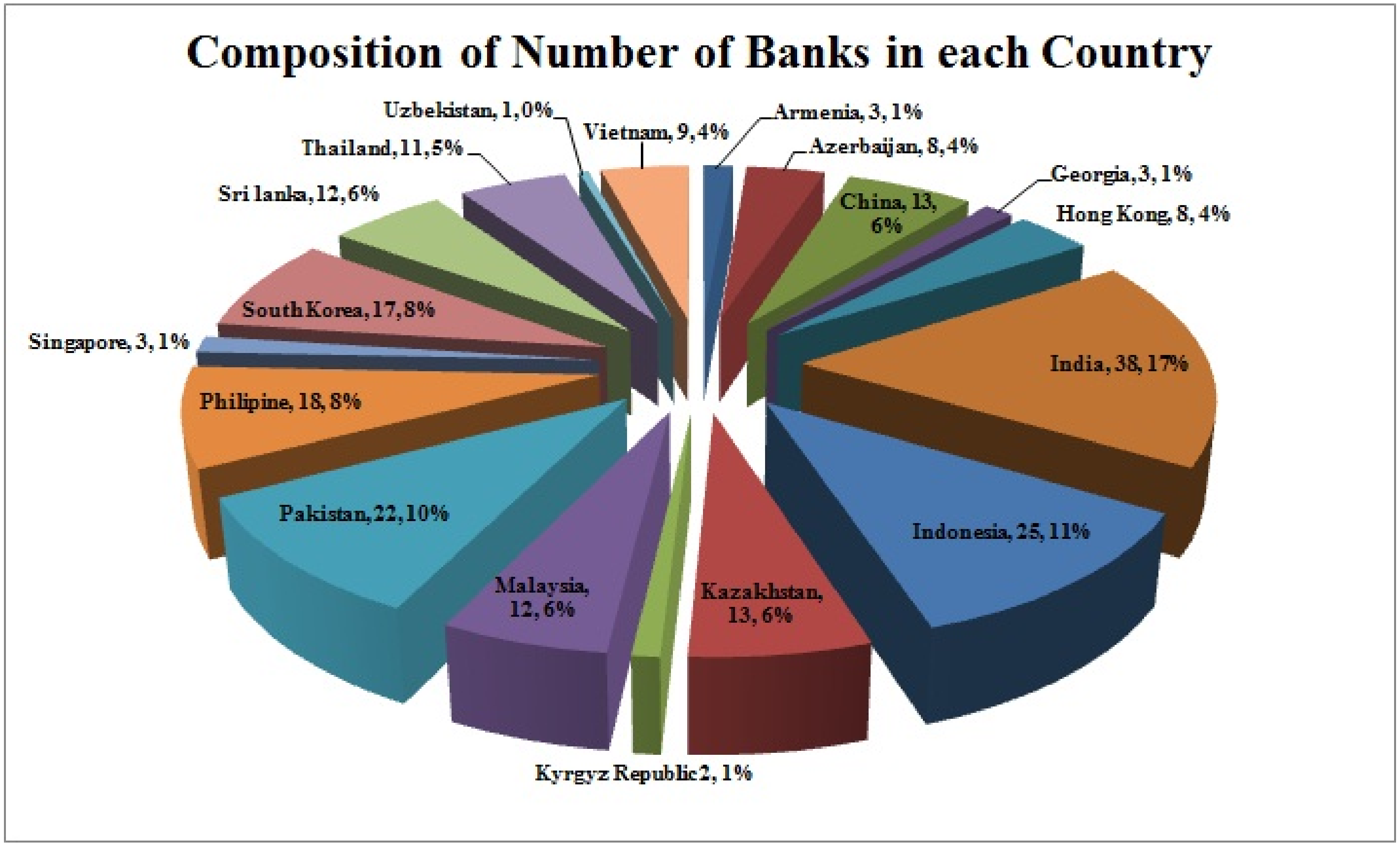

Figure 2.3: Composition of number of banks in different countries

2.6 Results

2.6.1 Descriptive Statistical Analysis

Figure 2.4 and Figure 2.5, illustrate the average trend of ROE and ROA for FIs for the 18 Asian countries in the data sample for the period between 1990 to 2010.

In 1999, with the start of the Asian crises[12] which affected nine big economies, ROE drastically fell down more than -13% at the peak of the crises and recovery to pre-crises level was completed by 2004.

Similarly, while examining the data, another drop in ROE and ROA can be seen with the start of the financial crises in 2007 and its peak in 2009 and 2008 where ROA and ROE dropped to less than 0.3% and 10%. Despite recovery, the trend appears to still be below the pre-crises level.

Although during both crises, the figures (specially ROE) shows a decreasing trend which started before 1999 for the Asian crises and before 2007 for the recent global crises. These trends show that most of the crises appear to have their first impact on financial markets where banks and financial institutions are major players.

Figures 2.6 and 2.7 and Table 2.2 and Table 2.3 show the

[12]The crisis commenced in Thailand with the financial collapse of the Thai baht. This occurred after the Thai government was forced to float the baht due to a lack of foreign currency to support its fixed exchange rate, cutting its peg to the USD, after exhaustive efforts to support it in the face of a severe financial overextension which was, in part, real estate driven. As the crisis spread, most of Southeast Asia and Japan saw a slump in currency, devalued stock markets and other asset prices, and a precipitous rise in private debt. Indonesia, South Korea and Thailand were the most affected countries by the crisis. Hong Kong, Malaysia, Laos and Philippines were also negatively impacted by the slump. China, Taiwan, Singapore, Brunei and Vietnam were, in comparison, less affected, although all countries suffered from a loss in demand and of confidence throughout the region. The effects of the crisis lingered through 1998 and the growth in Philippines virtually dropped to zero during the same year. Only Singapore and Taiwan proved relatively insulated from the shock, however, both countries suffered serious hits in passing, the former more so due to its size and geographical location between Malaysia and Indonesia. By 1999, however, analysts noticed signs that the economies of Asia were beginning to recover. Following the Asian Financial Crisis, economies in the region are working toward financial stability and on financial supervision.

trend of ROE and ROA with greater detail for each country. It can be seen, especially for the case of Thailand and South Korea, the ROE ratio dropped to -111% and -54.3%, respectively, during the peak of the crises in 1999. In addition, it is possible to note the impact of the recent financial crises of 2007, hitting its peak in 2008, when the ROE dropped to 10% with the country affected the hardest being Georgia. As one can understand from the average of ROEs, the recent crises had its origin in 2005 where it can be observed the start of a decreasing trend. This year is one year after the recovery of the Asian crises. Therefore, it can be concluded that profitability of financial institutions are worsened prior to the crises actually hitting the markets. On average, as shown in Table 2.2, the biggest figure for ROE occurred in 1994 at 18.7% and the lowest figure was recorded in 1999 when the Asian financial crises reached its peak. In 1999 ROE dropped to -13.8% with Thailand having to suffer the most.

Furthermore, mapping has been undertaken for the three groups of variables, financial (micro) and banking industry and macro variables with the ROA of FIs. These are illustrated in Figure 2.8. As it can be seen in the figure, variables which are expected to have a negative impact on profitability, tend to possess a counter-cyclical trend when compared to the trend exhibited by ROA. This means that when the variables display an increasing trend, profitability appears to present a decreasing trend and vice versa. Such variables are non-performing assets to total asset and average deposit interest rate. Non-performing asset ratio experienced recent peak in 2009, in time of a global financial crises. On the other hand, other groups of variables which are expected to have a positive impact on profitability showed a pro-cyclical trend with profitability over time. Such variables are net interest margin and GDP growth. Other variables, whose impact is expected to be mixed on profitability, exist, one example being, inflation. The sample appears to shows a negative impact for this variable. Inflation has a negative impact on profitability whenever banks are unable to compensate for the increase in inflation by adjusting their margins.

In Figure 2.6 and Figure 2.7 it can be seen that Thailand, Indonesia and South Korea as the most affected Asian economies. Moreover the counter-cyclical impact are more pronounced during the Asian crises period where counter cyclical variables of the profitability of banks such as inflation, non-performing assets and industry deposit rates had peaked and pro-cyclical variables such as GDP growth and net interest margins had demised to their lowest level in 1998. This is shown in Figure 2.8 .

It is worth noting that since two main structural breaks are shown in the time series, Asian crises with its peak in 1999 and the recent world financial crises with its peak in 2009, it is well-known that inappropriately omitting breaks can lead to misleading inference in time series testing. In respect to taking care of structural breaks, the first treatment is inclusion of dummy variables for the two structural breaks. However as far as panel data concerned, inclusion of time-invariant variables -representing structural breaks- are automatically being dropped from the panel regression model as result of collinearity. This happens because Panel regression models involve subtracting group means from the regressors. This means that only time-varying regressors can be included in the model. As dummies are constant within grouping variable and since the fixed effects estimator takes out all the variance at the group level, so there will be nothing left for the other dummies to explain. In other words, fixed effects regressions are time-invariant and theoretically have perfect multi collinearity with individual dummies. As employing time invariant dummies in order to take care of structural breaks is not possible in the panel regression model as result of collinearity, therefore another methods is called for.

As stated by Dobnik (2011), since the pioneering work of Perron (1988), it is well known that it is critical to allow for structural breaks when testing time series for unit roots. The failure to take into account the potential presence of structural breaks may lead to misleading inference regarding the order of integration. For instance, a stationary time series with a broken trend could be mistaken for a non-stationary process if the unit root test neglects the presence of structural breaks (Perron, 1988).

The investigation for several unit root tests which at the same time are taking care of structural breaks and dependencies between cross sections, shows that none are applicable to the data set analysed in this chapter which are characterized by three-dimension and strongly unbalanced format (more details are provided in Appendix D.1). Therefore the investigation to develop a proper unit root test for such unbalanced panels with long time series that include more than one break in left for future research.

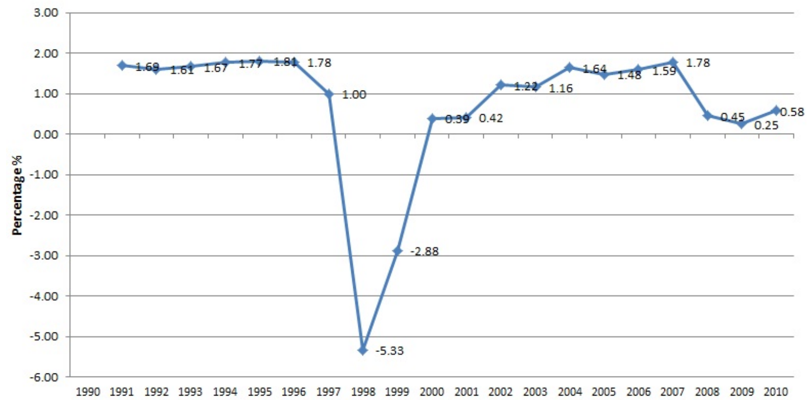

Figure 2.4: Trend of Return on Assets over time

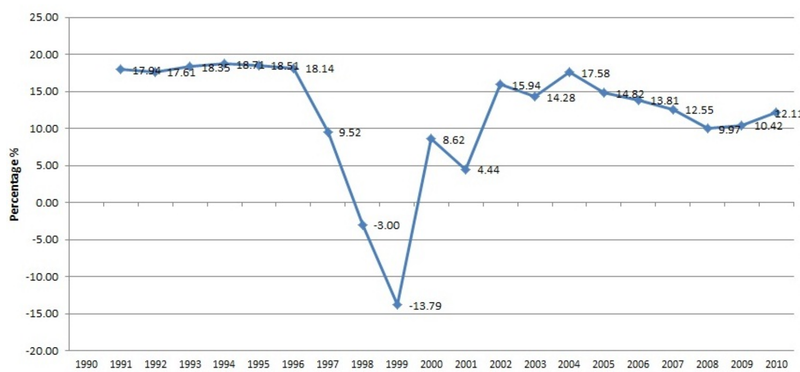

Figure 2.5: Trend of Return on Equity over time

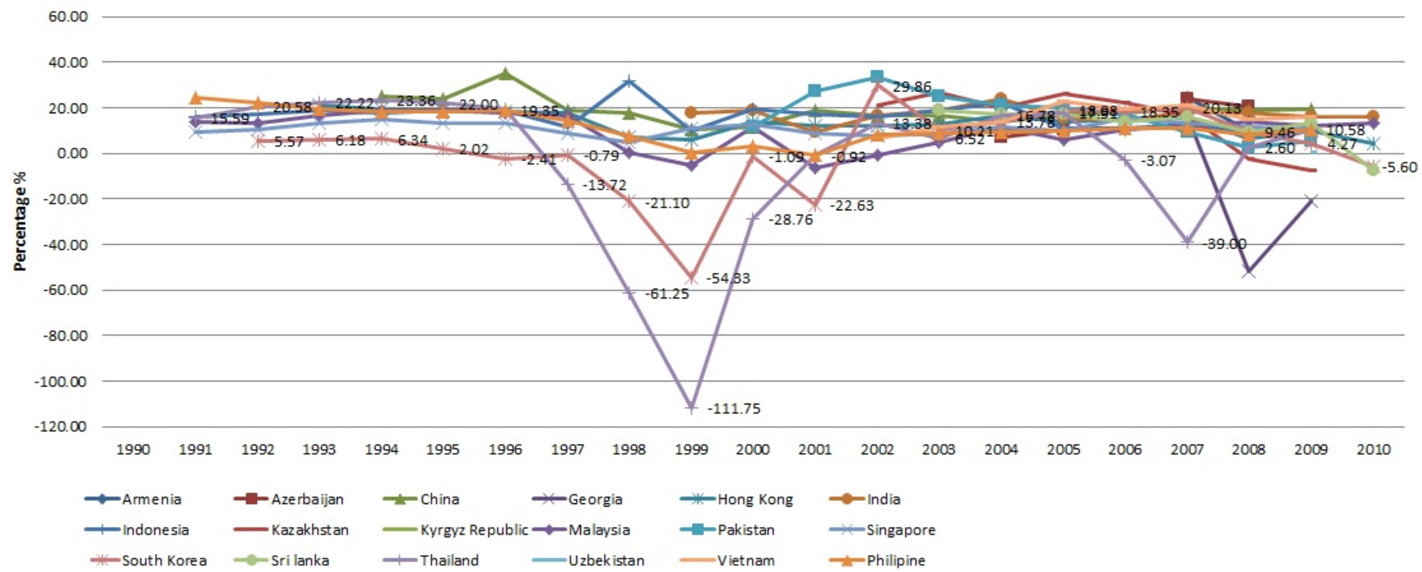

Figure 2.6: Trend of Return on Equity over time-country wise

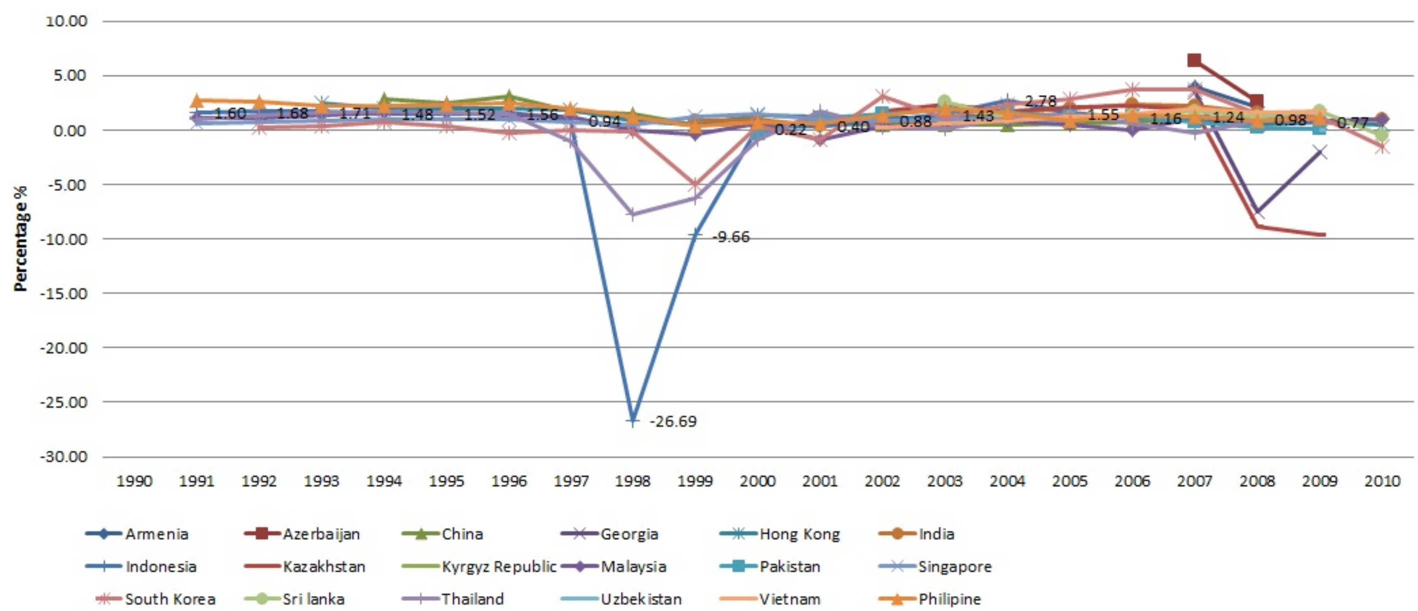

Figure 2.7: Trend of Return on Assets over time-country wise

Average of Return on Common Equity

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Grand Average
Armenia																	24.63	9.67			17.15
Azerbaijan														6.86	10.42		24.15	20.81			20.45
China				24.92	24.10	35.08	18.86	17.77	10.45	11.36	19.02	16.67	16.86	13.70	17.14	17.92	19.93	18.96	19.15		17.85
Georgia																	15.84	-52.04	-20.76		-25.95
Hong Kong			21.17	19.47	18.64	18.48	17.74	7.31	5.84	13.72	12.01	12.15	12.55	16.64	13.81	14.94	15.50	6.79	9.94	4.55	13.35
India									17.72	18.73	9.56	16.46	19.06	24.10	15.47	14.37	18.09	17.88	16.06	16.04	17.30
Indonesia	16.17	17.35	18.90	17.62	18.61	18.87	11.31	31.79	10.12	19.19	17.23	16.10	18.61	22.22	11.20	11.22	12.49	9.60	12.01		14.77
Kazakhstan												21.16	26.72	20.24	25.94	22.11	16.77	-2.52	-7.33		11.35
Kyrgyz Republic																		2.75			2.75
Malaysia	14.04	13.07	16.34	18.79	18.87	17.78	16.52	0.17	-5.45	11.48	-6.29	-0.91	4.63	11.49	6.15	10.30	12.10	14.09	12.31	13.45	9.74
Pakistan										11.53	27.35	33.70	25.16	21.20	19.97	17.24	9.09	2.42	5.20		15.26
Philipine	24.61	22.35	19.15	18.17	18.02	18.59	14.31	7.41	0.22	3.33	-0.76	7.98	8.88	9.53	9.61	10.93	10.99	8.18	10.48		10.86
Singapore	9.43	10.25	13.27	15.17	13.45	13.23	8.60	4.70	10.93	12.63	8.90	7.70	8.76	11.69	9.62	15.32	13.10	11.30	11.00		11.06
South Korea		5.57	6.18	6.34	2.02	-2.41	-0.79	-21.10	-54.33	-1.09	-22.63	29.86	10.21	13.78	18.98	18.35	20.13	9.46	4.27	-5.60	7.16
Sri lanka													18.99	17.38	17.14	13.62	16.04	9.16	13.11	-7.56	12.15
Thailand	15.59	20.58	22.22	23.36	22.00	19.35	-13.72	-61.25	-111.75	-28.76	-0.92	13.38	6.52	16.78	17.91	-3.07	-39.00	2.60	10.58		-0.36
Uzbekistan																			0.10		0.10
Vietnam												6.62	11.77	13.83	22.88	19.31	20.88	15.21	16.28		17.71
Grand Average	**17.94**	**17.61**	**18.35**	**18.71**	**18.51**	**18.14**	**9.52**	**-3.00**	**-13.79**	**8.62**	**4.44**	**15.94**	**14.28**	**17.58**	**14.82**	**13.81**	**12.55**	**9.97**	**10.42**	**12.11**	**11.97**
Maximum		Minimum																			

Table 2.2: Average of return on common equity

Average of Return on Assets	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Grand Total
Armenia																	4.0	2.1			3.1
Azerbaijan														1.0	1.7		6.3	2.7			4.4
China				2.9	2.4	3.1	1.7	1.5	0.5	0.6	0.6	0.4	0.5	0.5	0.6	0.7	1.0	1.0	1.0		0.9
Georgia																	3.5	-7.5	-2.0		-3.1
Hong Kong			2.5	2.0	2.0	2.0	1.9	0.8	0.5	1.3	1.2	1.2	1.1	1.5	1.2	1.3	1.2	0.5	0.8	0.4	1.3
India									0.8	1.0	0.4	0.8	0.7	1.6	1.9	2.3	2.2	1.7	0.8	1.0	1.5
Indonesia	1.6	1.7	1.7	1.5	1.5	1.6	0.9	-26.7	-9.7	0.2	0.4	0.9	1.4	2.8	1.6	1.2	1.2	1.0	0.8		-0.4
Kazakhstan												1.8	2.4	1.7	2.1	2.2	1.8	-8.9	-9.6		-2.8
Kyrgyz Republic																		1.0			1.0
Malaysia	1.1	1.1	1.4	1.6	1.6	1.4	1.2	-0.1	-0.4	0.6	-0.9	0.3	0.6	0.8	0.5	0.0	1.1	0.9	0.9	1.0	0.7
Pakistan										-0.4	1.1	1.5	1.9	1.6	1.2	1.2	0.7	0.2	0.1		0.9
Philipine	2.7	2.6	2.2	2.2	2.3	2.5	1.9	1.2	0.4	0.7	0.6	1.3	2.0	1.6	0.9	1.3	1.3	0.9	1.2		1.5
Singapore	0.6	0.7	0.9	1.0	1.0	1.0	0.8	0.5	1.2	1.4	0.9	0.8	0.9	1.1	0.9	1.4	1.2	0.9	0.9		1.0
South Korea		0.2	0.3	0.7	0.3	-0.3	0.0	-0.1	-4.9	0.4	-0.9	3.1	1.2	2.3	2.8	3.7	3.8	1.5	1.2	-1.5	1.5
Sri lanka													2.6	1.1	1.1	1.4	1.7	1.2	1.7	-0.6	1.4
Thailand	1.0	1.3	1.6	1.8	1.7	1.5	-1.0	-7.7	-6.3	-0.9	1.7	0.2	0.1	1.1	1.5	0.6	-0.3	0.8	1.0		0.0
Uzbekistan																			0.0		0.0
Vietnam												0.3	0.7	0.9	1.3	1.5	1.9	1.6	1.8		1.5
Grand Total	**1.7**	**1.6**	**1.7**	**1.8**	**1.8**	**1.8**	**1.0**	**-5.3**	**-2.9**	**0.4**	**0.4**	**1.2**	**1.2**	**1.6**	**1.5**	**1.6**	**1.8**	**0.5**	**0.3**	**0.6**	**0.8**
Maximum		Minimum																			

Table 2.3: Average of return on assets

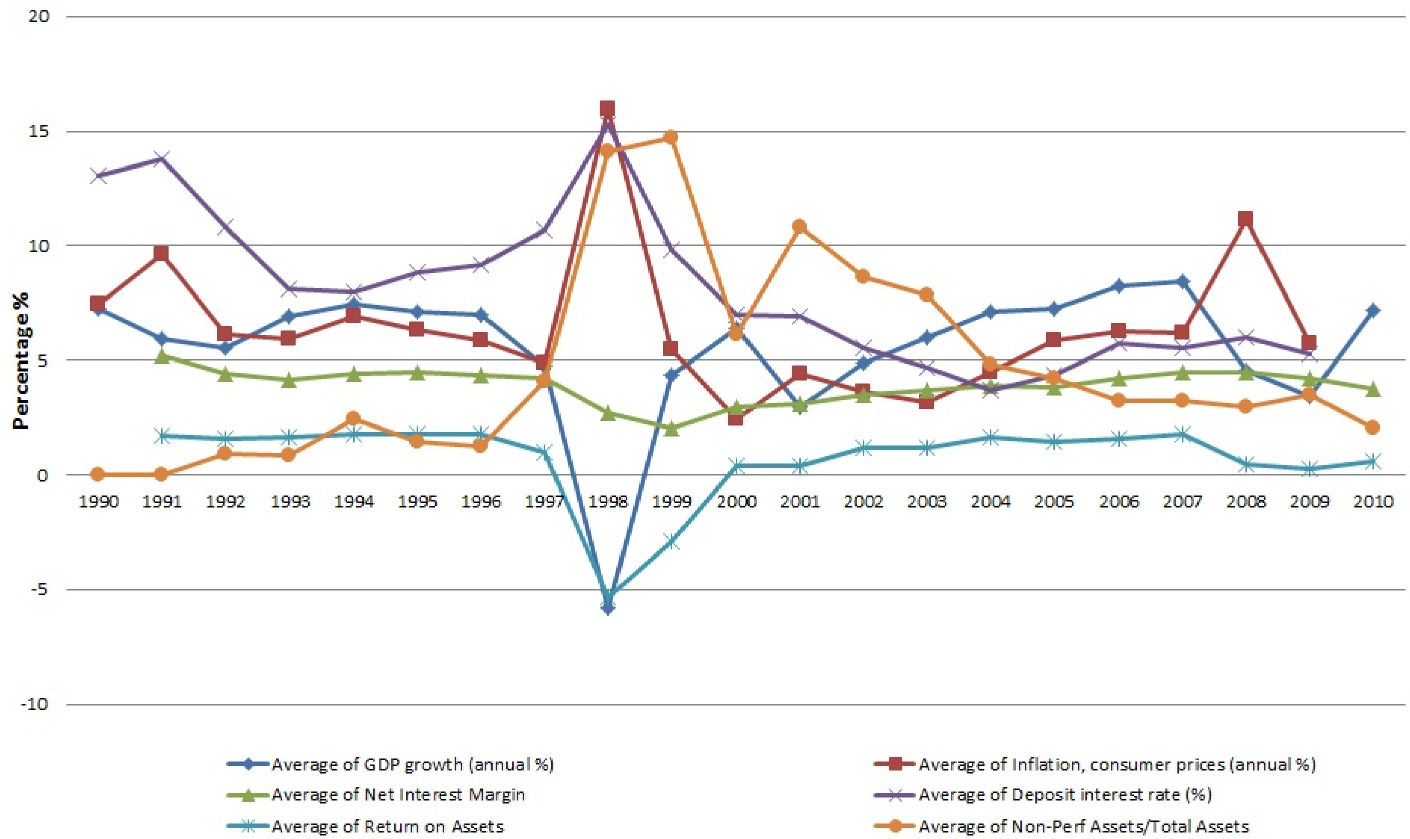

Figure 2.8: Trend of selective variables

2.6.2 Empirical results

As a first step for the estimation process, data for fixed or random effect is tested by employing a variance component model. This shows the variance in each group or at every level (countries, time and financial institutions) and is referred to as the base model in this study. When examining the second column of Table 2.6 which lists standard errors for the base model, one can decide whether to proceed with the fixed effect or random intercept model. For all three levels, the t-statistic is found to be significantly rejecting the null hypothesis that the groups are not different. This implies that one should proceed with random intercept model and with these results; it is now possible to imagine separate regression lines for each FI over time.

The second step is progressed by estimating four models. These models differ in terms of inclusion of different sets of explanatory variables. In Model 1, only bank-specific variables are added to the base model. In Model 2, industry-specific variables are added to Model 1. In Model 3, macroeconomic variables are added to Model 2 and finally, in Model 4, explanatory variables are made use of in Model 3 and allow for random slope coefficients.

By progressing from Model 1 to Model 4, the objective is to assess whether or not adding more explanatory variables leads to the construction of a "better" and robust model. In order to test this a Likelihood ratio test (LR)[13](Vuong, 1989) and Intra Class Correlation (ICC) ratio[14] The estimation results of the four models are presented in Table 2.6.

[13]The likelihood ratio test statistic is computed as $-2logL1-(-2logL2)$ which under the null hypothesis H_0 follows a chi-squared distribution with q degrees of freedom, where q is the difference in the number of parameters between the two models (Steele and Rasbash, 2009).

[14]Intra Class Correlation ratio shows how the total variance is distributed among levels, for example, how much total variance belongs to variation in country level, times level and FIs level (Moerbeek, 2004) is employed. ICC between countries; ρ_1 (within same countries, different time and different FIs) can be calculated as;

$$ICC = \rho_1 = \frac{\sigma_\nu^2}{\sigma_e^2 + \sigma_u^2 + \sigma_\nu^2}$$

Similarly, ICC between time; ρ_2 (within same countries, same time and different

In Model 1, bank-specific variables are included. The relationship between net interest margin and bank profitability is considered to be positive and provides support to the results of Demirguc-Kunt and Huizinga (2000), Huizinga and Demirg-Kunt (1999) and Holton et al. (2013). The positive results indicate that efficient cost management is a prerequisite for improved profitability for all banks. In other words, ensuring that a reasonable margin exists, possessing the ability to react to the market interest rates and being able to avoid fixed interest lending leads to a sounder margin. This is likely to result in more sustainable profits.

In reference to the impact of bank liquidity, loan to deposit ratio is unlike one's expectation. It is positively related to the profitability of banks, however, with a minor impact. These results are in contradiction with Hanweck and Ryu (2013) results which examined how bank funding structures have changed over time, especially, during the run-up to the crisis- and how these structures affect financial stability. Their analysis takes into consideration banks from a number of advanced and emerging market economies and includes systemically important banks. Their analysis shows that healthy banks rely more on equity and less on debt (especially short-term debt) and have a more diversified funding structures with lower loan-to-deposit ratios.

As expected, the impact of credit risk (non-performing assets to total assets as a proxy for credit risk) appears to have a negative relationship with bank profitability, implying that banks possessing more non-performing asset will exhibit less profitability since more provisioning will be required. Another justification for such a negative relationship, as stated by Hou (2005) is that "increased non-performing loans can cause the decline in commercial bank credits, as banks with high level of non-performing loans in their portfolio may become increasingly reluctant to take up new risks and commit new loans".

Price to book value per share is another financial ratio that has

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FIs) can be calculated by using the following formula;

$$ICC = \rho_2 = \frac{\sigma_u^2 + \sigma_\nu^2}{\sigma_e^2 + \sigma_u^2 + \sigma_\nu^2}$$

a significant and positive effect on profitability. As also reported by Athanasoglou et al. (2006) "during the boom in stock market, total profits and particularly those resulting from financial transactions, exhibited a significant increase (more than 100%)." Also as stated by Keat and Young (2008) "Stock prices are a reflection of a company's profitability. If managers do not seek to maximize profits, stock prices fall and firms are subject to takeover bids and proxy fights[15]." The primary role of the stock market is to act as a barometer for financial health. Analysts relentlessly scrutinise companies, and this information affects the traded securities of companies. Therefore, creditors usually look favourably upon companies whose shares perform strongly. This preferential treatment is, in part, due to the link between a company's earnings and its share price. Over the long term, strong earnings are a good indication of the company's ability to meet debt requirements. As a result, the company will receive cheaper financing through a lower interest rate, which in turn increases the amount of value returned from a capital project. Subsequently, this results in more profitability for the firm. Alternatively, favourable market performance is useful for a company seeking additional equity financing. If there demand exists, a company is always able to sell more shares to the public in order to raise money. Essentially, this process is similar to printing money, and this is not necessarily damaging for the company - as long as it does not dilute its existing share base excessively, in which case, issuing more shares can have disastrous consequences for existing shareholders.

Model 2 is progressed by adding industry-specific variables, such as deposit interest rate to Model 1. Deposit interest as a proxy for monetary authority interest rate policy, has a negative effect on profitability. This is due to an increase in the cost of borrowing for credit customer, which reduces the numbers of profitable projects. It is

[15] An event that occurs when the stockholders of a corporation develop opposition towards some aspect of corporate governance, often focusing on directorial and management positions. Corporate activists may attempt to persuade shareholders to use their proxy votes to install new management for variety of reasons. Shareholders of a public corporation may appoint an agent to attend shareholder meetings and vote on their behalf. That agent is referred to as the shareholder's proxy.

known that there is an adverse relation between interest rate and the investment in an economy. Therefore monetary authorities by increasing the interest rate, decreases the number of projects that meet the minimum internal rate of return (IRR) for investments, compared with the cost of credit. The results are supportive of the results produced by Hanweck and Ryu (2005) where they found that, for most bank groups[16] which were considered, after-tax earnings were less sensitive to interest-rate changes than NIM are, however, the degree of sensitivity differs amongst banks with different product-line specialties.

For Model 3 macro-economic variables are added to Model 2. Inflation (consumer price index), as expected, negatively impacts on profitability. The negative impact implies that the management of banks are unable to fully forecast future inflation levels, which in turn indicates that interest rates have not been adjusted appropriately to achieve higher profits. This may also be viewed as a result of the success of bank customers (opposed to bank managers) to fully anticipate inflation, implying that above normal profits could not be achieved from asymmetric information. Most studies undertaken suggest an ambiguous impact of inflation upon profitability (see Athanasoglou et al. (2006)). The impact of GDP growth on profitability, as expected, appears to have significant effect which is positive. This is due to the requirement for additional money being circulated which results in more lending and therefore, more profitability. This result is consistent with the findings of most of studies such as Vong and Chan (2008), Naceur (2003), Tan and Floros (2012) and Valentina and McDonald (2009). In order to fully analyse and understand other remaining country related effects, dummy variables are used. Two variables are employed: development status of countries (developed and developing) and the exchange change regime of countries (categories include free float regime, managed float regime, different types of currency pegging). The results demonstrate that a "developed" status appears to have a negative effect on the overall profitability and countries with a managed float regime appear to have a positive

[16] Their sample covered 12 different bank groups based on the specialisation and asset size of the bank at the end of each quarter.

impact on profitability. The effect of exchange rate fluctuations on profitability of banks, as shown by Demirguc-Kunt and Detragiache (1997) depends on the ability of FIs to protect themselves against speculative attacks. In addition, as reported by Moody's, the effect of currency depreciation has a direct impact on a corporation's immediate liquidity - where interest or principal payments are due in the near future when there is clearly little time for reversal of the exchange rate movements. Therefore, countries with managed float exchange rate regimes are more relatively more secure in managing exchange rate fluctuations when compared to countries with free float regimes.

In Model 4, random slopes of explanatory variables are tested. A systematic procedure is used where explanatory variables are allowed to have random slopes at their own or upper levels[17] and the model is run until convergence is achieved and coefficients are estimated.

In Table 2.6 the random effect is shown in the bottom portion of the table. As mentioned, descriptive variables can be allowed to be random in their related level or upper level. For instance, after testing the random slope of the explanatory variables, it is found that net interest margin is random at time and FI level and price book value per share to also be random at time level. Modelling them as a random slope led to the explanatory power of the model being increased enormously. Therefore, variance-covariance matrixes or interactions between intercept and variables for three levels are shown. For instance in Model 4, at time level, interactions between intercept and slope[18] of net interest margin is -5.61 implying that the higher the magnitude of intercept for FIs, lower the slope of net interest margin variable. This is similar to the time level, which indicates the same pattern for each point in time.

Comparison of models using likelihood ratio test and ICC ratios allows the selection of the best model (Table 2.4). In terms of likelihood ratio, it can be noticed that -2logL for base model (15,921) decreases significantly to 5,168 for Model 4. For Model 4, the intra-country correlation decreases to 0 from 5.81 for the base model. Therefore,

[17]FIs' variables (financial ratios) can be made random at the country level, however, it is not possible to make related variables for countries (macroeconomics), whether time variant or time invariant (dummy) to be random at the FI level.

[18]Positive implies, more the intercept, more the slopes of the variable.

according to these criteria, Model 4 is selected as the "best" model in terms of explanatory power.

	Base Model	Model 1	Model 2	Model 3	Model 4
Intra Country Correlation	5.81%	5.32%	0.63%	0.54%	0.00%
Intra Time Correlation	28.77%	5.63%	16.00%	14.68%	41.26%

Table 2.4: Intra Class Correlation ratios for ROE as dependent variable

	Base Model	Model 1	Model 2	Model 3	Model 4
Intra Country Correlation	0.55%	2.30%	1.46%	0.00%	0.00%
Intra Time Correlation	23.43%	26.49%	8.74%	6.25%	13.06%

Table 2.5: Intra Class Correlation ratios for ROA as dependent variable

2.6.3 Robustness checks: alternative measure of bank profitability

In order to verify robustness of the results, return on equity is replaced with return on assets as the dependent variable. The results are presented in Table 2.7. It is worth noting that all regression models perform reasonably well with almost all coefficients of baseline variables staying same: they maintain the same sign and remained significant as they were in the models with ROE as dependent variable. However, the value of -2logL for Model 4 is 2746 which decreased significantly from 11,000 for the base model. In addition, when ROA is used as the dependent variable, the coefficient on exchange rate regime and price to book value per share lose their explanatory power in most of the estimated regression models. Moreover, similar to the original model the ICC ratios (see Table 2.5) allow for Model 4 being selected as the best model.

	Base Model	S.E	Model 1	S.E	Model 2	S.E	Model 3	S.E	Model 4	S.E
Fixed Part										
Constant	11.131*	1.764	3.713***	2.502	5.437***	2.607	13.085***	7.078	16.422**	7.213
Net Interest Margin			2.105*	0.442	2.16*	0.492	2.176*	0.506	2.258*	0.571
Non Performing Assets to Total Assets			-0.51*	0.114	-0.896*	0.148	-0.896*	0.147	-0.808*	0.112
Total Loans to Total Deposits			0.011*	0.005	0.026*	0.006	0.026*	0.006	0.029*	0.006
Price to Book value per Share			1.626*	0.575	0.547***	0.659	0.394***	0.67	2.075**	1.341
Deposit Interest Rate					-0.278***	0.26	-0.55**	0.371	-0.531**	0.254
Consumer Price Index 2005(100)							-0.073**	0.066	-0.102**	0.04
GDP Growth Annual							0.375**	0.31	0.145*	0.223
Developed							-2.582***	4.031	-4.074**	2.717
Managed Float Regime							2.086***	2.688	1.354***	1.912
Free Float Regime							-1.176***	4.122	-0.587***	2.448
Random Part										
Level: Country Level										
$\sigma^2_{v,\,Constant}$	28.906***	16.794	19.102***	13.284	2.343***	6.201	0.507***	4.887	0	0
Level: Time										
$\sigma^2_{u,\,Constant}$	143.23*	20.21	62.251*	15.021	59.973*	17.291	52.959*	16.098	119.698*	48.596
$\sigma_{u\ Constant,\ Net\ Interest\ Margin}$									-14.278***	9.661
$\sigma^2_{u,\,Net\ Interest\ Margin}$									10.694*	2.999
$\sigma_{u\ Constant,\ Price\ Book\ Value\ per\ Share}$									-45.799***	26.709
$\sigma_{u\ Price\ Book\ Value\ per\ Share,\ Net\ Interest\ Magin}$									-23.566*	6.553
$\sigma^2_{u,\,Price\ Book\ Value\ per\ Share}$									114.644*	22.585
Level: Financial Institutions										
$\sigma^2_{e,\,Constant}$	325.759*	11.457	277.862*	14.32	312.48*	18.832	313.386*	18.89	170.443*	32.927
$\sigma_{e\ Constant,\ Net\ Interest\ Margin}$									-5.61***	6.202
$\sigma^2_{e,\,Net\ Interest\ Margin}$									-0.098***	0.924
-2*Loglikelihood	**15921.467**		**7410.409**		**5568.334**		**5563.57**		**5168.168**	
Units: Number of Countries used	**18**		**11**		**9**		**9**		**9**	
Units: Number of Years Used	**206**		**126**		**105**		**105**		**105**	
Units: Number of Financial institutions Used	**1811**		**862**		**640**		**640**		**640**	
(* for 1%, ** for 5% and *** is for 10%)										

Table 2.6: Result of regression with ROE as dependent variable

	Base Model	S.E	Model 1	S.E	Model 2	S.E	Model 3	S.E	Model 4	S.E
Fixed Part										
Constant	0.721*	0.236	4.249*	0.606	4.403*	0.659	7.808*	1.459	2.938*	0.567
Net Interest Margin			0.312***	0.029	0.825*	0.048	0.835*	0.049	0.391*	0.064
Non Performing Assets to Total Assets			-0.118*	0.009	-0.095*	0.010	-0.092*	0.010	-0.027*	0.006
Total Deposits to Total Assets			-0.055*	0.007	-0.06*	0.008	-0.055*	0.007	-0.015*	0.006
Deposit Interest Rate					-0.315*	0.032	-0.356*	0.042	-0.101*	0.014
Consumer Price Index 2005(100)							-0.028*	0.008	-0.013*	0.002
GDP Growth Annual							0.056**	0.039	0.034**	0.015
Developed							-1.054*	0.502	-0.611*	0.179
Managed Float Regime							0.461**	0.351	0.218**	0.155
Free Float Regime							-0.191***	0.509	-0.31*	0.162
Random Part										
Level: Country Level										
$\sigma^2_{v,\,Constant}$	0.138***	0.284	0.274***	0.303	0.139***	0.161	0.000	0.000	0.000	0.000
Level: Time										
$\sigma^2_{u,\,Constant}$	5.877*	0.894	3.151*	0.617	0.831*	0.307	0.57*	0.249	2.255*	0.754
$\sigma_{u,\,Constant,\,Net\,Interest\,Margin}$									-0.503*	0.172
$\sigma^2_{u,\,Net\,Interest\,Margin}$									0.113*	0.040
Level: Financial Institutions										
$\sigma^2_{e,\,Constant}$	19.07*	0.659	8.468*	0.408	8.534*	0.471	8.553*	0.471	15.007*	1.128
$\sigma_{e,\,Constant,\,Net\,Interest\,Margin}$									-3.191**	0.261
$\sigma^2_{e,\,Net\,Interest\,Margin}$									0.693*	0.061
-2*Loglikelihood	**11037.25**		**5015.00**		**3767.00**		**3751.55**		**2746.85**	
Units: Number of Countries used	**18**		**11**		**9**		**9**		**9**	
Units: Number of Years Used	**206**		**129**		**108**		**108**		**108**	
Units: Number of Financial institutions Used	**1865**		**977**		**745**		**745**		**745**	

(* for 1%, ** for 5% and *** is for 10%)

Table 2.7: Result of regression with ROA as dependent variable

2.7 Concluding remarks and direction for future research

In this study, an empirical framework has been specified to investigate the effect of bank-specific, industry-specific and macroeconomic determinants on the profitability of banks for 18 Asian countries. Using the unbalanced data, an attempt to examine the determinants of bank profitability in Asian countries over the period 1990-2010 has been made by testing several banking, industry and macro-economic variables. This has produced 4 models which have used annual financial data from 218 banks in 18 countries (which are all borrowing members of Asian Development Bank) resulting in 2112 observations.

For estimation, a two-way random effect panel model has been used. The results show that net interest margin as proxy of efficiency, non-performing loan to loans as proxy of asset quality, loan to deposit as proxy of liquidity and price book value per share as proxy of sensitivity to market have significant impacts on profitability which have been defined as bank specific variables. For industry specific impacts, industry deposit interest rate has been employed which shows to have a significant impact on the profitability of banks. The other sets of variables, such as GDP growth rate and inflation rate, represent macro-economic variables, show a strong impact on the profitability of the banks. The impacts of the variables appear to show compatibility with existing literature. Moreover, some new dummy variables such as exchange rate regime type, as well as development status of the economy on profitability have been defined and tested. Results shows that countries with free float exchange rate regimes are exposed to increased volatility in profitability.

The findings of this study has considerable relevance to policy since the identifications of profitability drivers can help forecast future financial status of the FIs by using forecasted macro-economic, banking industry data and budgeted financial statements of FIs. Such models can assist and play a role of a dynamic system for the assessment of FIs and help detect financial fragility before occurrence.

For instance, it has been found that net interest margin is one of the determinants for profitability of FIs. Therefore, a large proportion of long-term, low margin loans on the balance sheets of banks indicate that rebuilding net interest margins and overall profitability is likely to be a long, drawn-out process. As a result, FIs require awareness of adverse results by booking the bulk of their credit portfolio with fixed interest rate and long terms loans. This could lead to rigidity in their interest income compared to their interest expense (if they bear short-term liabilities) in case of a sudden change in interest rates in the economy. The negative impacts can occur upon decreasing net interest margins (in worst case scenarios can also include negative net interest margins) which result in lower profitability/loss or even if continued for several years in succession, it could result in the bankruptcy of FIs. Therefore, FIs always require careful consideration of interest rate, in both their asset and liability sides at all time. In most banks, the (Asset Liability Management) ALM unit is responsible for these issues.

Similarly, it is found that the adverse relationship between the profitability of banks and regulated deposit rates. The findings imply that an understanding of the systematic effects of changes in interest-rate on bank NIM are likely to help in better prepare for variations in contingent liability associated with adverse developments in the macro-economic and financial market environment. As such, one can refer to abrupt/sudden increase of the interest rate by regulatory authorities as one of the monetary instruments to neutralize FX speculation attacks.

The other issue which banks need to consider is the share of NPL in their credit portfolio. On most occasions, in order to achieve unusual targets such as growth in lending, FIs start to behave in an aggressive manner and increase their lending activities. However, in cases where the bank does not possess sufficient resources of credit officers to undertake appropriate due diligence analysis of customers, it results in a high portion of non-performing loans. This translates to high loan loss provisioning and the writing-off expenses which decreases profitability and in extreme cases, could result in decreasing the equity of the bank. As also stated by Capitaine et al. (2013), in the current challenging economic environment it is essential that banks, under the control of their statutory auditors, keep paying a close attention to the early identification and classification of non-performing loans, in order to ensure that assets are prudently valued and impairment provisions are rigorously recognised.

Other policy relevant fact is understood from the adverse effect of countries with a free float exchange rate regime. This means that such countries are more vulnerable in time of speculative attacks. In such times, banks which carry FX loans in their liability side and when loans are not hedged appropriately are likely to face severe repayment problems. This is because of their revenue being in local currency and because of their requirement to pay debts in FX (amount that has now appreciated).

It was also found that a high inflation rate and high GDP growth rate can be translated to higher profitability for banks. In this regard, by predicting the level of GDP growth and inflation rate for upcoming years, it is also possible to predict banking system profitability and adjust their monetary and fiscal policy, accordingly.

The results of this research may also be used for asset classifications. Future research can attempt to include governance variables such as taxation, regulatory indicators as well as indicators of the quality of services offered. In addition, the size of FIs e.g. small, medium and large banks, types of financial institutions e.g. commercial banks, saving, industrial, development banks and shock dummy variables such as pre-crises, crises and post crises also can be modelled by employing different methodologies, such as using dynamic panel models.

Chapter 3

Determinants of firm performance: effect of macro-economic and organisational factors

3.1 Introduction

The main objective of this study is to improve the understanding of main determinants of the performance behaviour of firms. In addition, this study is related to broad sets of theoretical and empirical research.

With a broader demand for investment, whether in the stock market or in corporate bonds or other types of investment in companies such as equity participation, the ability to make wise investment choices is the underlying reason why judging profitability of firms as a key performance indicator is crucial. Secondly, from the perspective of lenders, it is necessary for financial institutions to analyse firms before commencing any business activities. Therefore, possessing knowledge of the main determinants related to the performance of firms becomes more crucial.

In industrial economics, there are two different approaches to explain corporate performance. One includes structure-conduct-performance (SCP)[1] (Schmalensee, 1989) and other are firm-effect models. Briefly,

[1]The structure conduct performance (SCP) paradigm, first published by

the SCP type of models argue that an exogenous market structure determines corporate behaviour and performance, while in firm-effect models, the profitability of firms is the sole result of firm characteristics.

In respect to the motivation behind this paper, and the contribution of this study to past literature, a mixture of the following is employed: Structural-Conduct-Performance (SCP) models and firm effect model to investigate firm profitability using a dynamic panel model which incorporates firm and macro-economic level variables by using data of companies from 17 European economies in transition over the recent 10 year period. Return on asset (ROA) as a dependent variable is selected and tests are undertaken for several variables which are grouped as liquidity, efficiency and leverage ratios e.g. net working capital turnover, payable period, interest coverage ratio and several macro-economic variables such as GDP growth, inflation rate and several indicators of privatised environments such as banking system reform and the level of stock market capitalisation. It is believed that drawing conclusions on the implications and effects of these variables will provide further insight into the relationship between financial statement data and profitability. Secondly, a more recent and updated time horizon (2003-2012) is examined with a larger set of data (approximately 21,000 observation which averaged for each year for each country) and compared to past studies. Thirdly, data for companies from 17 Central and Eastern European counties is made use of. These countries, which are in transition (instead of analysing single countries, unlike past studies such as Raheman and Nasr (2007) for Pakistani firms, Stierwald (2010) for Australian firms, Stephan

economists Edward Chamberlin and Joan Robinson, and developed by Joe S. Bain is a model in Industrial Organization Economics which offers an informal theoretical explanation for the performance of firms through economic conduct in incomplete markets. According to the structure- conduct-performance paradigm, the market environment has a direct, short-term impact on market structure. Then, market structure appears to have direct influence over the firm's economic conduct - which in turn affects its market performance. Therein, feedback effects occur in such a manner that market performance may impact conduct and structure. In addition, conduct may affect market structure. Additionally, external factors such as legal or political interventions affect market framework and, by extension, the structure, conduct and performance of the market.

and Tsapin (2008) for Ukrainian firms, Brush et al. (1999), Hansen and Wernerfelt (1989), Nagy (2009) and Powell (1996) for firms from United States, Guilmi (2008) for Italian firms, Demir (2009) for Turkish firms, Muia (2009) for Kenyan firms, Lee (2005) for Korean firms, Slade (2003) for Swedish firms, Prasetyantoko (1997) for Indonesian firms, Majumdar and Bhattacharjee (2010) and Surajit (2008) for Indian firms. This approach can be considered as being original and does not appear in existing literature, which covers the post-privatisation period. In addition, macro-economic factors are included and employ a fixed and random effect model to fully understand the effects of different countries. All variables show a significant effect and all expected effects appear to be in line with theory.

Moreover, the results of this study can be utilised in simple scorecard models for setting factors weights, as well as in more complicated methods e.g. fuzzy techniques, to form a degree of support for each membership function variable.

The remained of this study is structured as following: the next section includes performance related indicators of firms. Section 3 reviews the literature and Section 4 explains the employed data sample. Section 5 examines a dynamic model of corporate profitability, while Section 6 demonstrates the empirical results using random and fixed effect regressions. Finally, Section 7 presents the conclusions of this study and offers suggestions for further and future research.

3.2 Performance of firms in countries experiencing transition in the context of post-privatisation

Privatisation is considered as transferring a firm's ownership from state to non-states shareholders. This process began in the West with the denationalisation program in the United Kingdom, under the leadership of Margaret Thatcher. The practice then spread to other industrialised states and developing countries. Numerous countries that have experienced privatisation range from Asian countries such as China, Latin American countries, African countries such as Egypt and central and Eastern European counties, which the later are a focus of this study. This privatisation of public enterprises is becoming increasingly common throughout the world due to the globalisation of market principles. This wave of privatisation experienced during the past two decades has provided evidence that it has had a positive impact on operating efficiency of firms operating under privatised environments. However, there are several exceptions, for instance as reported by Frydman et al. (1999) privatisation in Russia has failed to improve the performance of firms, when they did not have significant ownership or control by outsiders[2]. Nevertheless, a vast amount of literature exists using data from the 1990's and that which investigates the effects of privatisation of such insider and outsider shareholders factors on the performance of companies, although, in this study, the focus is placed on other aspects of privatisation. An investigation that factors except acquisition and ownership by insiders and outsiders such as banking reforms and stock market developments, which imply that a privatised environment can influence the performance of firms, is undertaken.

In this section, the behaviour of firms in a post privatisation period is examined and then the focus shifts to intra-organisational and macro-economic environments in which firms operate.

3.2.1 Privatisation and performance of firms

As mentioned previously, privatisation can be expected to have significant impacts on the performance of firms. In fact, the ultimate objective of privatisation appears to be to release firms from the grip of corrupted, inefficient state ownership and management to transform into more productive and profitable firms. Although, as stated by Megginson and Netter (2001) privatised firms are more efficient and profitable than state owned firms, however, this depends on the method of privatisation undergone. This study empirically tests this hypothesis by employing dummy variables for method of privatisation and investigates the impact on the performance of firms. In Table 3.1

[2] Outsiders, in this instance implies, parties other than employees and managers who own companies shares.

it is shown countries in respect to their method of privatisation and the date of their privatisation. Although countries used a variety of methods to privatise, the approach used by Bennett et al. (2007) will be categorising firms based on their predominant method of privatisation. Since privatisation is often coupled with other economic reforms, such as trade and stock market liberalisation and banking reforms, such variables are used as indexes for privatisation.

Country	Classification of Privitization Method	Year of Privitization
Bosnia	Voucher	1999
Bulgaria	Voucher	1993
Crocia	MEBO	1992
Czech	Voucher	1992
Estonia	Sale	1993
Hungary	Sale	1990
Lativa	Sale	1992
Lithuania	Voucher	1991
Macedonia	MEBO	1989
Moldova	Voucher	1995
Montenegro	Voucher	1989
Poland	Sale	1990
Romenia	MEBO	1992
Serbia	MEBO	1989
Slovekia	Sale	1995
Slovenia	MEBO	1998
Ukraine	Voucher	1995

Table 3.1: Countries and their dominant method of privatisation

Banking reform; Fiscal decentralisation reforms along with liberalisation; privatisation and stabilisation reforms have been undertaken by several countries in transition over the past decades. Crivelli (2012) argues that "decentralization may aggravate fiscal imbalances, unless the right incentives are in place to promote fiscal discipline." He attempts to answer a central question, whether or not privatisation helped to promote fiscal discipline of local governments. He found a negative result when privatisation was considered in isolation. Elsewhere, Fries and Taci (2002) state that "reforms are clearly required to overcome some of the legacies of socialist banking if it leads to the development of sound, market-oriented banking systems." Both refer to the scale of banking activity, such as level and growth of lending and deposits taken by banks, as indicators of banking development.

Banking reforms represent a change from a socialist banking system toward the creation of institutional standards and norms of an industrialised market economy, as represented by the Basel Committee's Core Principles on Effective Banking Supervision and Regulation (see Fries and Taci (2002)). Asset share of foreign owned banks are employed as an indicator for banking reforms, which can be expected to have positive impacts on the performance of companies. This trend can be seen in Figure 3.4

As stated by Crivelli (2012) banking sector reforms (including privatisation) have also taken place in Eastern Europe at different speeds and with particular characteristics. Most economies undergoing transition have introduced reforms aiming to increase the size, stability, and efficiency of their banking sectors. Moreover, substantial liberalisation has been introduced to induce competition and increase intermediation; establish sound banking supervision to allow foreign financial institutions to operate competently and banking environment and legislation has been updated to reduce credit risk and enhance transparency. As reported, an illustration of the success of the banking reform process is the impressive decline in the share of non-performing loans in the economy from an average of 18.5% in 1999 to an average of 3% in 2007. In addition, during the past decade, interest rates and the intermediation of bank spreads declined, leading to a substantial increase in the ratio of private credit to GDP, from 30% to above 40% of GDP in Central and Eastern Europe, while doubling from 10% to 20% in CIS countries. Therefore, it is expected that banking reforms through increased lending to individuals and corporates increase the performance of companies.

Development of Capital Market: On most occasions, an active and well developed capital market allows newly privatised firms to have greater access to capital frequently required for further restructuring and facilitates modernisation. Therefore, the level of capital market development can be an important determinant of post-privatisation efficiency gains. As reported by DSouzaa et al. (2004)

firms whose shares trade in more sophisticated and active equity markets ought to display the strongest improvements in performance. In addition, stock market liberalisation is associated with lower costs of equity and higher economic growth rates. Stock market capitalisation as percentage of GDP is used as index of capital market development and the positive impact on the performance of firms is expected. This index (Figure 3.3) has shown similar pattern as profitability indexes which shows growth trends over the years, except for the year 2007, when it dropped drastically due to global financial crises.

Methods of privatisation

Central and Eastern European countries are characterised by using three methods of privatisation: a)through sales of assets, b)transferring the ownership to the firm's management or employees called management employee buyouts (MEBO) and c)through distribution of vouchers which is also referred to as mass privatisation. Each of these methods has their own advantages and disadvantages. These are explained in more detail, justifying why a particular method is chosen rather than others towards the achievement of privatisation.

Share Issue Method/Sales of Assets; Evidence from Hungary
This method is characterised by selling part or all of the state owned enterprises (SOE) to investors through public share offering. Advantages of this method include the ability to raise substantial amounts of money for the government, which, in all likelihood, assists in the development of market capital. Disadvantages of this model are that the process is time consuming and requires consultants, advertising and underwriting, inspection expenses incurred by the governments before the shares are sold. The process of using this method involves three steps and challenges, namely: how to transfer control, how to price the offer and finally, how to allocate the shares. This method of privatisation requires the existence of a developed capital market and has some comparative advantage over other methods. These include the rationale behind why the method can be used in some situation rather than in others circumstances. In most case share prices of SOEs are under-priced in relation to market price, which will allows

investors to make a premium on top of their investment. As reported by Iwasaki et al. (2010) unlike Russia and the Czech Republic, Hungary avoided giving away public assets to private interests as much as possible. Instead, the country pursued the direct sale of public assets to strategic investors, including foreigners. This privatisation strategy was, in principle, applied to all industries across the country. As a result, almost all of the 1,859 former socialist enterprises designated in 1990 as "to-be-privatised" firms had transferred to complete private ownership or liquidated by the end of the 1990s. In addition, foreign investors bought and successfully restructured the public enterprises that were suffering financially before privatisation. However, if appropriate policy frameworks were in place, there may have been a chance for Hungary, one of the largest foreign capital recipients among the former socialist countries, to be able to receive further benefits from foreign direct investment (Iwasaki et al., 2010).

MEBO; Experience of Romania Management-Employee Buy-out is a type of privatisation model, where ownership transfers to the firm's managers and employees who are called insiders. As such, within countries which have used this method of privatisation, Romania has the largest percentage of insider dominated firms (see (lmos Telegdy, 2002)). As reported by lmos Telegdy (2002) this method has its supporters and its critics. Supporters of insider ownership argued that profit sharing and participation in during the decision making process has positive effects on the performance of firms, while the opposing group argue that ownership of insiders leads to the reluctance of the workforce to restructure the company, especially in relation to initiating layoffs, one of the harmful methods of restructuring. However, most analysts agree that outsider ownership is superior to insider ownership, especially in large, heterogeneous firms, where the decision making process of workers can be slow and costly. In addition, workers may find it more difficult to obtain funds for investment, when compared to outsider investors. As stated by (lmos Telegdy, 2002) it is difficult to decide whether or not Romania was not able to attract investors - both domestic and foreign- or whether political constraints faced by the government hampered sales of state owned companies, on an individual basis. Therefore, as reported by lmos Telegdy (2002) both the small demand for state-owned companies' shares and political constraints were present which resulted in direct sales being under-utilised, especially during the first several years of transition, until 1995 when the MEBO method was used exclusively. Later this privatisation technique did not cease to play an important role in diminishing state ownership. As he discusses the preferential aspect of the program is the credit granted by the State Ownership Fund (SOF) for the purchase of the shares, usually with a highly negative real interest rate. The granted debt could be paid back from the company's profits, the company is exempted from profit tax during the repayment period, and the responsible organisation for the repayment of the debt was the Employees' Association (Program for Shareholder-Employees, PAS in Romanian). Therefore, in order to be eligible to the preferences set in the law, the current management, employees and retired workers whose final workplace was in the company, formed this organization which besides paying back the loan, adopted the ownership rights and duties of the company. If the voting rights in the PAS had been distributed according to the shares owned by its members, then the company may have been either a managerial buyout (when the management of the company owns more shares than the non-managerial employees), or an Employee Stock Ownership Plan (ESOP), if the workers had majority. However, there were heavy restriction such as change in employment, change in the primary activity of the firm and sale of shares of privatised firms with this method of privatisation in Romania. This of course, had a consequence of further diminishing the possibility of restructuring, which consisted of a greater problem in insider owned firms, relative to traditional enterprises, owned by outsiders (lmos Telegdy, 2002).

Voucher; Evidence from Ukraine This model, also known as mass privatisation, was usually common in Eastern Europe and was the method whereby eligible citizens of a nation could use vouchers that were distributed free of charge or at a nominal cost. This method provides holders with the right to bid for stake of SOE's or other assets that have been privatised. Experience has also shown that it does not provide for an effective ownership structure for new privatised (state owned enterprises) SOEs, instead, insiders end up controlling the majority of the more valuable companies and ordinary investors receive claims of only the weakest and least promising SOEs. The disadvantages of this method include:

- No cash inflow is raised for the government or firms and therefore no transfers of technology occurred and a lack of capital and expertise from foreign investors or multinational companies to the privatised companies.

- No encouragement for the new owners of the privatised firms who were the existing managers and employees, little or reduced incentives to effectively restructure the operation of firms and the reduction in staff numbers in order to cut cost.

- In most cases, governments never fully gave up control of important privatised companies to private owners because the governments were still of the opinion that firms had significant strategic value to be left unsupervised. This was because government wanted to ensure that no serious cuts in staff numbers would occur.

- Government also made newly privatised firms to continue to enjoy soft budget constraints for an infinite amount of time.

For an example of countries that used such a method. Ukraine can be referred to, where the process of privatisation began in 1992. At that time, privatisation appeared to be the major item on the agenda of Ukrainian reformers and it was the first step in the process of transition towards a market economy. Low popularity of reforms among Ukrainians, the dominance of communist bureaucracy within the highest bodies holding power and the lack of private capital, seemed to contribute to the unlikelihood of "big-bang" reforms taking place. Therefore, a mass privatisation approach (Vouchers) was chosen in order to provide for the fastest method of transfer of ownership from the public into private hands, and to guarantee the irreversibility of transition reforms. Voucher privatisation was carried out with substantial distortions, which caused negative impacts for the entire privatisation process. The idea of "fair" distribution of property rights among all citizens of Ukraine, obviously, could not assist in the implementation of one of the primary goals of privatisation - the improvement of enterprise efficiency (see Galyna and Stefan (2004)). A diluted ownership structure that was formed because of mass privatisation led to deteriorative effects on the incentives provided to managers. Managers had little incentive to launch efficiency enhancing restructuring programmes, fearing that the process will lead to worker and shareholder lay-offs. Furthermore, since the free circulation of privatisation certificates was prohibited, illegal forms of circulation contributed to the enlargement of unofficial sectors of the economy. Finally, overall bureaucratisation of the mass privatisation process and the lack of transparency also blocked successful reforms from being implemented (see Galyna and Stefan (2004)). Therefore, the entire privatisation process can be characterized as being non-transparent and bureaucratised, while the state still owns large stakes in partially privatized enterprises.

Impact of privatisation on the performance of firms

When government bureaucrats manage SOEs, often the objective appears to be to only balance between providing social welfare for the people and achieving their own objectives, such as patronage, nepotism. This is in contrast with what occurs in the private sector, which operates solely for profit maximisation. Generally, one may refer to private sector development, attracting foreign direct investment, fostering competition and contributing to the formation of stock markets as consequences of privatisation. In addition, privatisation may improve the performance of individual enterprises. As it is assumed, once firm starts or continues its operation in a private setting, it will be subjected to strong, constant and challenging pressure to perform efficiently since it now faces a more competitive business environment. The firm struggles for scarce resources and market share in order to survive. As explained previously, methods of privatisation are crucial in achieving the targets of efficient and profitable companies. As explored, economies, which had used vouchers and MEBO as their major method of privatisation, were unsuccessful to transform into profitable companies. This is unlike countries, which used other methods of privatisation, such as the sale of company assets to foreigners. This study will test this statement during the post-privatisation period using an empirical model.

It can be argued that in most cases, privatised firms will not perform better when compared to SOEs, except in conditions where, due to the competition created (as a result of privatisation which leads to increased market pressure), private firms strive to survive within the market environment to avoid being taken over or becoming bankrupt.

In order to detect the impact of privatisation on the performance of firms, dummy variables for privatisation methods are employed and it is expected that voucher and MEBO methods will negatively influence upon the performance of firms, while the sale method will have a positive influence. The first two methods lead to the acquisition of the firm by the insiders, who have no incentives to improve the performance.

Generally, developed stock markets are able to ease the privatisation process; therefore, stock market capitalisation as a percentage of GDP has been employed as capital market development index.

Since privatisation occurred in the context of economic and financial reform, other variables can be employed as privatisation indexes, which include asset shares of state owned banks, asset shares of foreign owned banks, banking reform and budgetary subsidies. These variables shows improvement starting form 1989 until 2011, therefore their impact on the performance of firms performance, using an empirical method, will be undertaken.

However other than privatization environment, the performance of firms is impacted by intra-organisational decisions and the country's macro-economic environment such as the level of expansionary monetary policies in which the firm is operating with.

3.2.2 Performance of firms as result of organisational policies

After controlling for the privatization, influencing performance, other endogenous factors such as intra organisational factors that can have an impact on the performance of firms are examined. As such, endogenous variables referred to are liquidity and the efficiency profile of corporate entities under consideration. The aim of this research is to identify which variables contribute towards better financial performance of firms. Groups of organisational factors demonstrate the internal strategy of companies. For instance, collection periods and payable periods, limits the amount of cash and working capital the company requires in fulfilling market demands and the profitability persistence. These are all considered as endogenous organisational or firm level factors. In this sub-section variables as determinants of profitability are listed, tested and explained.

Liquidity Ratios Liquidity is defined as the ability of a company to meet its short-term obligations and it is a key measure of financial health. Five main liquidity ratios exist, namely: current ratio, quick ratio, cash ratio, collection and payable period.

Accounts payable to the cost of goods sold ratio (payable turnover) measures how a company pays its suppliers in relation to the cost of goods sold. Multiplying the inverse of this ratio by 365 provides the payable period that indicates the average number of days a company has before paying its suppliers. Logically, the higher the payable period, the company has greater ability to convince their creditors to pay with some allowance for delay and be able to employ those funds to conduct and undertake further operations. However, Raheman and Nasr (2007) found opposite results indicating the negative impacts of payment days on the profitability of firms by arguing that less profitable firms appear to wait longer before paying their bills.

Efficiency Ratios The quality of receivables of businesses, how efficiently the company is able to use and control its assets, how effective it is in paying its suppliers and whether the business is overtrading or under-trading on its equity, are all measured by efficiency ratios. Four key financial ratios to measure a company's efficiency are as follows: inventory turnover ratio, assets to sales ratio, sales to net working capital ratio, return on asset, net profit margin ratio and the cost of employee/operating revenue.

Net working capital turnover is defined as sales divided by net working capital, shows the amount of cash required to maintain a certain level of sales or the number of sales dollars earned for each company's net working capital. It is important to maintain a certain level of cash used by a company at a minimum level, in order to ensure that its financing needs are reduced. This ratio is most effective when tracked using a trend line. It enables the management to note if there are long-term changes for cash required by the business, in order to generate an equal amount of sales. This ratio will deteriorate (decrease) due to specific management led decisions. These include situations where a company has elected to expand its sales base to less creditworthy customers, and it is likely that they will pay with delay when compared to regular customers, thereby increasing the company's investment in receivable accounts. Moreover, an alternative usage for this ratio is during budgeting purposes - where budgeted working capital levels can be compared to historical amounts of this ratio to observe whether a sufficient budgeted working capital level exists. Sutanto and Pribadi (2012) found that net working capital turnover has a positive impact on the profitability of firms.

The Cost of Employee/Operating Revenue is often referred to as the efficiency ratio, and is primarily used by companies to measure efficiency in terms of employee expenditure and expenses. This ratio measures operation efficiency by comparing the cost of employee as a proportion of the total revenue. In other words, by dividing costs of employees by the amount of revenue, the employee cost-to-revenue ratio indicates the level of human resources required to generate a dollar of revenue. Employee costs include everything from employee salaries, employee benefits and pension expenses. To achieve higher revenue, firms may have to commit more employee cost resources, which, on occasions, may not have an immediate effect for the improvement of operational efficiency, however, there may have a negative effect on profitability during the short run. Therefore, it is necessary for firms to be cost efficient. In general, the employee expense-to-revenue ratio provides guidance for control and a tool to achieve improved expense management.

Leverage Ratios A company's leverage relates to how much debt it has on its balance sheet and it is another measure of financial health. Generally, the more debt a company possesses, greater the risk to its stock, since debt holders have the first claim rights of a company's assets. This is important because, in extreme cases, if a company goes into bankruptcy, there may be nothing remaining for its stockholders after the company has satisfied its debt holders. It can be stated that debt to equity ratio, equity to asset and interest coverage ratio are major leverage ratios.

Debt/Equity ratio measures the proportion of the company that is financed by its debt holders when compared with its shareholders. A company incurring a huge debt is likely to reflect a very high debt/equity ratio, while one with little debt, will possess a low debt/equity ratio. Debt-to-equity ratio is calculated as the sum of short term and long term debts, divided by shareholders' equity and it is a measure of a company's financial leverage. Nagy (2009) argues that a high debt-to-equity ratio tends to mean that a company has been aggressive while financing its growth with debt, which can create volatile earnings. This puts a company's stock at more risk since it does not appear to be a conservative investment. Although as a basic principle in finance, greater risk equates to greater potential returns therefore one might expect a high debt-to-equity ratio to generate a higher ROA, however, like R and D, the effects of debt-to-equity are not tangible in short term returns. Theoretically, it is expected that this ratio will be negatively correlated with ROA for the same fiscal year.

Interest Coverage ratio; the entire borrowing of companies in the form of debt incurs interest charges. Interest coverage ratio measures a company's ability to meet its financial expenses with the income generated from the firm's primary source of business. As higher interest coverage ratios are better, the interest coverage ratio close to or less than one indicates that the company is facing serious difficulty in paying interest. It is calculated as operating income over interest expense.

Equity/Asset ratio is one of numerous financial ratios used to help determine the financial health and long-term profitability of a corporation. It is often used by investors to determine whether or not the shares of a corporation can be considered as safe investment. Though important, equity-to-assets ratios should be used only with other financial ratios to determine a corporation's overall financial health. This ratio relates to the value of the corporation's equity, divided by the value of its assets. A high ratio indicates that the corporation is primarily owned by its shareholders, while a low ratio indicates that the corporation is likely to be burdened with high debts. An equity-to-assets ratio value below 0.70 generally presents difficulties for a corporation to borrow money, due to solvency concerns. However, this ratio is misleading for prospective investors under certain circumstances. A corporation might experience high levels of debt to take advantage of emerging business opportunities, or it may reinvest loan revenues into an investment offering higher returns compared to the interest it pays on debt. Likewise, a high equity-to-assets ratio does not necessarily mean that the corporation enjoys sound financial health; it may in fact be falling behind its competitors in an industry, which requires high levels of investment and cannot be financed using equity alone. Stephan and Tsapin (2008), Stierwald (2010), Raheman and Nasr (2007) and Yoon and Jang (2005) use debt to asset as the other form of the mentioned ratio. This is calculated as 1 minus equity to asset ratio.

3.2.3 Macro-economic environmental impact on the performance of companies

Other than company strategy, exogenous factors which affect the company performance, irrespective of their internal policy structures, exist. Therefore, macro-economic factors might be noteworthy examples of such exogenous factors. In this regard, for instance, as a country is growing, the entities operating inside the country are simultaneously growing, therefore GDP (employing GDP growth as proxy) can have positive effects on the profitability of companies (Muia, 2009).

Moreover, macro-economic studies have proven to be extremely useful to researchers in providing a basic theoretical perspective on the influence of macro-economic environments on firm strategy and performance. Performance of companies is expected to be sensitive to the macro-economic environment and its impact on the risk faced by companies has recently been highlighted in literature. For instance, McNamara and Duncan (1995) and Muia (2009) found a positive relation between percentage change in GDP and one period ahead of ROA. This study uses GDP growth rate as an index for cyclical output effects and it is expected that this factor has a positive impact on the profitability of companies. As GDP growth rate slows down, particularly during a recession, operations of a firm decrease leading to the reduction in company's returns. More specifically, as stated by DSouzaa et al. (2004), in the context of privatisation of a privatised firm during a period of overall economic growth (perhaps brought about by greater trade liberalisation, advantageous capital market conditions, or a combination of factors other than privatisation) may experience improved performance during the post-privatisation years. Therefore, performance improvements may be primarily driven by a favourable macro-economic environment and not due to change in ownership. As an attempt to control the macro-economic effect, the regressions presented in this study include a variable measuring the actual change of overall economic growth for each country, measured by the annual GDP growth.

Macro-economic risks are also accounted for by controlling inflation, as measured by the GDP deflator rate. The extent to which inflation affects the profitability of firms depends on whether future movements in inflation are fully anticipated, which, in turn, depends upon the ability of firms to accurately forecast future price movements. An inflation rate that is fully anticipated may results in raised profits since firms are able to appropriately adjust their prices to increase revenues. However, if inflation is not predicted accurately and in a timely manner and as a result sale prices are not adjusted accordingly, a negative relationship is expected between inflation and the performance of firms (see Prasetyantoko (1997) for similar results). The variables employed and the expected impacts are presented in Table 3.2.

Dependent Variable		Variable Return on Assets	Expected effect
Determinnats	Organizationa Factors	**Efficiency**	
		Sales/Net working Capital	+
		Costs of Employees/Operating Revenue (%)	-
		Lag ROA	+
		Liquidity	
		Payables Period or Credit Period	+
		Leverage	
		Interest Coverage Ratio	+
	Macroeconomic factors	GDP Growth	+
		Inflation, GDP Deflator	-
	Privitization Factors	Asset share of Foreign-owned banks (in percent)	+
		Stock market capitalisation (in percent of GDP)	+
		Method of Privatization (Sale of Assets)	+
		Method of Privatization (Voucher, Mass Privatization)	-
		Interaction between GDP Growth and Method of Privatization (Sale of asset)	?
		Interaction between GDP Growth and Method of Privatization (Voucher)	?

Table 3.2: Variables and their expected impacts on the profitability of firms

3.3 Literature review

In literature, two main approaches exist to explore the determinants of the performance of firms. One is based on an economic perspective, which identifies the external market factors as main factors in determining the success of firms, while the other area of research focuses on intra-organisational factors. This study seeks to extend the scope of the existing body of literature. As the following will be explained, researchers have previously examined the impact of financial soundness, grouped as liquidity, efficiency, macro-economic, and ownership structure aspects of privatisation on the performance of firms in different countries. Therefore, the aim of this study is to explore whether or not results from previous research will be reproduced for the set of Central and Eastern European countries in the post-privatisation period.

A number of studies that have investigated the impacts of leverage on the performance of companies, Yoon and Jang (2005), found a positive relation between leverage factors and the profitability of firms operating in the restaurant industry. However, their findings are in contradiction to the findings of Hirschey and Wichern (1984) where it was found that higher leverage results in greater risk. This tends to reduce the discounted present value of the future profit stream. These negative findings are similar to the findings of Nagy (2009), where the study found that debt to equity levels and dollar value of capital expenditures have a negative impact on ROA employing data from 2003-2007 for S and P 500, which represent the premier 500 companies in United States.

The size of the firms, another main determinant of the performance of firms, is considered by Yoon and Jang (2005). The study found a positive relation between the size of firms and their performance.

Other intuitional factors such as research, development intensity and TV advertising was investigated by Hirschey and Wichern (1984) who found a positive impact on profitability, unlike Nagy (2009) findings which reported that advertisement expenses have no impact on profitability. An additional part of existing literature suggests considering the persistent effect of profitability on performance of firms. As such, research containing the work undertaken by Nagy (2009), employs ROA as a dependent variable and attempts to investigate the persistency of this variable using the ROA for the past three years. A positive impact on the profitability was observed.

Stephan and Tsapin (2008) attempt to identify the main drivers of the performance of firms and attempt to quantify their importance employing a panel set of large Australian companies for the period between 1995 and 2005. The estimated dynamic profit regression model, unlike most found in existing literature, directly includes measures of productivity and productivity persistence. Estimation results are similar to the studies of Hansen and Wernerfelt (1989) and Brush et al. (1999) which indicate that the profitability of firms is influenced by intra-organisational characteristics and sector effects are relevant, but to a smaller extent. Their analysis also reveals that, among institutional effects, productivity and productivity persistence intensify profitability.

Similarly Majumdar and Bhattacharjee (2010) investigate the relative importance of firm and industry effects on corporate profitability over a 16 year period using data from 3000 Indian firms. They found that the effect of firms is significant in all periods and these become more pronounced over time. While the industry effect does statistically matter, in general, it is significantly large in the period after comprehensive liberalisation compared to other periods, suggesting that industry choice is also a consideration within competitive markets for firms to enjoy above average profitability.

In another sets of studies Hansen and Wernerfelt (1989) employed the integration of institutional factors and macro-economic factors. The results confirm that both sets of factors are independent and important in explaining the performance of firms. In addition, it was also found that organisational factors explain around twice as much variance of the profitability of firms when compared to exogenous economic factors. Their findings are similar to the study undertaken by Brush et al. (1999) which concludes stating that corporations have a greater influence on the profitability of firms compared to the industry. Similarly, Powell (1996) in his research attempts to prove that industry is important in explaining corporate performance using data from 166 companies located in North Eastern USA. The findings support the results from earlier studies, which found that industry membership explains roughly 20% of financial performance. He concluded by stating that "not all of the 80% of unexplained performance variance is attributable to firm-specific resources since some will also be attributable to shared generic strategies, strategic group membership, other shared resources, or chance".

Following a similar approach, Demir (2009) made use of semi-annual data from 1993 to 2003 pertaining to 172 manufacturing companies in Turkey and explores the impacts of external shocks, macroeconomic uncertainty and country risk on the profitability of real sector firms after controlling the share of financial investments in total assets. The study suggests that in order to sustain profit margins when exposed to higher risks, competition and uncertainty, most real sector companies, generally, invest in liquid financial assets rather than long term fixed assets. In addition, the research estimates a dynamic panel model, which indicates that increasing uncertainty, real interest rates, country risk and capital flow volatility are found to have a significant negative influence on the profitability of manufacturing firms. In contrast, the findings demonstrate that the rise in short-term financial investments reduce the negative impact of volatility, risk and higher interest rates. Finally, the study concludes suggesting that firms generally make use of short-term investments as a method of hedging themselves against uncertainties and market risks.

Another different approach involves the investigation into impacts of such factors by employing data for a set of countries. For instance, Guilmi (2008), by performing a hazard function analysis and by employing data for 7 European countries between 1992 and 2003, attempts to explore the stochastic relationship between profits and financial structures. The study shows that leverage influences profitability with different degrees for each nation.

Other than the above mentioned studies, which are concerned about intra-organisational factors and general macro-economic environments, studies that attempt to investigate the performance of firms in a specific context, such as countries in transition, exist. Therefore, investigating the effects of privatisation on the performance of firms is the focus of a large body of current research. Numerous researchers have investigated such factors. For instance, a study undertaken by Iwasaki et al. (2010), is an attempt to explore the impacts of privatisation on the performance of firms in Hungary. This study examines the effects of ownership transformation from the state to the private sector on firm performance in the post-privatisation period using annual data from Hungarian enterprises for the early 2000s. The study examined the effects of ownership transformation from the state to the private sector in relation to privatised firms in the post-privatisation period focusing on the Hungarian enterprises in the early 2000s. The study found that foreign investors appear to outperform domestic investors within a short period with regard to medium and small-sized SOEs sold in the early 2000s. This was the period of large-scale privatisation when foreign direct investment made a significant contribution towards the restructuring of large Hungarian corporations. In another instance, Galyna and Stefan (2004), investigate the impact of privatisation on the productivity of Ukrainian firms. The empirical research is based on a sample of 466 Ukrainian joint-stock enterprises for the period between 1997 and 1999 and the estimation results indicate that privatisation not only positively influences labour productivity, but also that the effects diminish over time. Similarly, labour productivity appears to be positively influenced by an increase in competition. The researchers argue that privatisation, even if not implemented to 100 precent, increases performance if it leads to majority private ownership. Moreover, the justification for the negative impact of a number of years since privatisation is that, the benefits diminish over time. In most probability, this indicates that private firms will continue to benefit from state ties and may lose-out if those ties are cut-off completely.

Loc et al. (2006) have produced valuable findings in relation to privatisation in Vietnam. The study suggests that the Vietnamese privatisation programme, which launched in 1992, differs from standard Western privatisation programmes in terms of the residual percentage of shares being owned by the state and the portion of shares owned by insiders. Their study measures the impact of privatisation on the performance of firms by comparing the pre and post-privatised financial and operating performance of 121 former state-owned enterprises (SOEs). The regression analysis reveals that firm size, residual state ownership, corporate governance and stock market development are the key determinants for performance improvement. Also found are that profitability (measured by income before tax on assets, income before tax on sales, and income before tax on equity), efficiency (measured by real sales efficiency and income efficiency), real sales, and employee income appear to increase significantly following equitisation. These findings are in line with growing empirical evidence, which demonstrates that firms become more profitable and efficient following privatisation. In addition, their finding show significant negative effects of size on the change in profitability and efficiency measures, thus supporting the hypothesis that smaller firms may be more flexible during the necessary adjustment process, following privatisation. A significant negative relationship exists between state ownership and the change in before-tax income, and between state ownership and the change in income efficiency. Similarly, the regression analysis reveals that firms who have a chairperson of the board of directors who represent the state, experience a significantly lower increase in real sales, sales efficiency, income efficiency, and employment compared to firms where the appointment of the chairperson of the board of directors is from the private sector. Overall, the empirical results of the study suggest that equitisation in Vietnam works in the sense of improving firm performance, in terms of most performance measures.

Another study by Frydman et al. (1999) analysed profitability behaviour for countries such as the Czech Republic, Hungary, and Poland and tested several impacts of variables on the performance of firms in countries undergoing transition. The study made use of data based on a survey of 506 medium-sized manufacturing firms conducted in the fall of 1994. Tests were undertaken for revenue, employment, productivity and cost/revenue ratio as dependent variables and employed privatisation effects, country effects, group effects as descriptive variables. It was found that on occasions where outsiders owned privatised firms, it had more than a fourfold impact on revenue, but a one-third effect on employment. Moreover, the research found that insiders are likely to be less productive and incur more cost to revenue ratio. From these results, it was concluded that the effects of privatisation on corporate performance, while often quite powerful, are not automatic or uniform across different types of firms or different performance measures. In the context of economies undergoing transition in Central Europe, this means that privatisation is effective in enhancing revenue and the productivity performance of firms, which are controlled by outsider-owners. However, no significant effect is produced for firms, which are controlled by insiders.

Past literature (see Figure 3.3 for examples), in relation to the profitability of firms, is extensive and over the course of time has addressed several missing components, as well as crucial flaws and loopholes in previous models and methodologies. To date, economists still acknowledge there is sufficient scope for further research in this area. For instance, investigating macro-economic and industrial factors requires further research and work. In addition, most studies made use of data from single and not from multiple countries to detect country related effects. Therefore, in this regard, this research is original work to understand and investigate the performance behaviour of firms, taking into account countries in transition in the context of the post-privatisation period.

	Sample (data base, years, restricitons)	Method	Unit of analysis	Independent Variables used	Dependant Variable	Countries of Coverage	Source of data
Raheman and Nasr (2007)	1999-2004 (6 years), 94 companies	Panel Analysis	Financial sector, banking and finance, insurance, leasing, modarabas, business, services, renting and other services are excluded from the sample	Number of day's accounts receivable, number of days inventories, number of days accounts payable and operating income, Average Collection Period (ACP), cash Conversion Cycle (CCC), Current Ratio (CR), Size (Natural logarithm of Sales (LOS)), Debt Ratio (DR) and ratio of financial assets to total assets (FATA).	Net Operating Profitability (NOP), It is defined as Operating Income plus depreciation, and divided by total assets minus financial assets.	Pakistan	KSE
Stierwald, A. (2010)	1995 to 2005 (9 years), 961 large Australian firms	Dynamic profit model using GMM method	Discretionary, Energy, Financials, Health, Inforamtion, Industrials, Materials, Staples, Telecommunication, Utilities.	Industry and Firm specific variables	EBITDA.	Australian firms	Integrated Real-Time Equity System (IRESS) and suplemented by Australian Bureau of Statistics (ABS) and the Australian Securities and Investments
Stephan and Tsapin (2008)	1999-2006 (7 years), 3000 firms	GMM	Mining, Food, Textile, Wood Processing, Chemicals and Oil Chemicals, Consturction Materials,Metallurgy, Electronic, Tools, Machinery, Processing, Energy, Construction and Transport	Ownership %, Ownership status (corporate or individual)	price-cost margin (PCM), which is definded as revenue minus costs relative to revenue, and return on assets (ROA), which is defined as operating pro ts divided by the assets of the firm.	Ukranian	SMIDA (State Commission on Securities and Stock Market) database, which is comprised of the balance sheets and income statements of open joint stock Ukrainian companies during 1999 2006.
Demir (2009)	bi-annual data from 1993 to 2003 for 172 manufacturing firms	dynamic panel estimation techniques-GMM	Manufacturing firms	Profitability from operational activities measured as the operating profits divided by net fixed assets	Operating profit to net sales ratio.	Turkey	Istanbul Stock Exchange Market database
Yoon and Jang (2005)	1998 to 2003, 372 company-year observation	OLS regressions	Restaurant firms	Firm size, financial leverage	ROE	United States	Mergent Online database and the Yahoo Finance
(Muia, 2009	1999 – 2009, 32 firms	Multiple linear regression equation	Financial and Industrial	Firm characteristics: Profitability Industry variables: Sales growth, Industry concentration Market variables: Stock market index, GDP growth	Growth in EPS	Kenya	Nairobi Stock Exchange
Lee, J. (2005).	1993 to 1997.	Fixed effects model is used.	primary, light manufacturing, heavy and chemical,manufacturing, construction, electricity and gas, sales, transportation, communication, personal and business service, and	dummy variable representing the presence of labor union, log value of total asset, advertising-sales ratio,, fixed asset to sales ratio, dummy variable representing affiliation with thirty largest chaebol and dummies for industries	PROFIT = (operating income)/(total assets - investment assets).	Korea	Korea Listed Company Association
McNamara and Duncan (1995)	1978-1991, 41 firms	GLS regression	All sectors	real GDP (GDP_R), the Treasury Note rate (IR_TNOTE), and aggregate corporate profits after tax (COYPAT)	ROA	Australian firms	Macro economic data was obtained from the DX Statistical Data Base at Bond University.
Prasetyantoko (1997)	1994-2004, 238 listed companies	Ordinary Least Square (OLS)	All sectors	Firm Size = natural logarithm of total assets in Rupiah at the constant price Controlling variables: 1. Leverage: total debt/equity 2. Liquidity: Short-term debt/ total debt (STD/TA) 3. Solvency : short-term assets/short-term debt (STA/STD) 4. Interest rates 5. Inflation 6. capital market development	1. Rate of return on assets (ROA), (EBIT) / total assets. 2. Market Capitalization growth	Indonesia	Jakarta Stock Exchange (JSX)
Majumdar and Bhattacharjee (2010)	1985 and 1991, 3187 firms	variance decomposition	All sectors	Company effects, industry effects, time effects, industry multiply by time interaction effects	ROA	India	Reserve Bank of India (RBI) database on financial accounts of non-government public limited companies.
Sutanto and Pribadi (2012)	Monthly financial data January 2008 to December 2009	Multiple regression analysis, t-test, F-test, coefficient of determination, partial correlation, and classical assumptions.	Single company data	Net working capital turnover, current ratio, receivable turnover and net working capital turnover	ROA	Indonesia	The data are the monthly financial reports from January 2008 until December 2009 of a company namely CV. Tools Box.
Guilmi (2008)	1992-2003,	Weibull parametric hazard function	All sectors	Equity Ratio	ROA	France, Germany, Greece, Italy, Spain, Sweden, United Kingdom	Amadeus database

Table 3.3: Literature Review

3.4 Methodology

According to literature such as Raheman and Nasr (2007) and Stierwald (2010), the specification below allows for lag-dependency in profitability and the contribution of firm characteristics, macro-economic and privatisation environments in explaining firm profits. In a summarised form, the basic model is described as:

$$\pi_{it} = f(\pi_{i,t-1}, X_{i,t}, t) \qquad i = 1, 2, ..., m, t = 1, 2, ..., n \tag{3.1}$$

where $\pi_{i,t}$,$\pi_{i,t-1}$ represent current and lagged profitability for average[3] of firms for country i at time t. As expected, final year profitability has an effect on current profitability and therefore its lag is included in our model which implies for a dynamic[4] component in profitability. The term $X_{i,t}$ contains a set of firm characteristics such as liquidity and efficiency ratios, macro-economic variables and privatisation effects. A linear dynamic model of firm profitability takes the expanded form of:

$$\pi_{it} = \alpha + \beta\pi_{i,t-1} + \delta X_{i,t} + \epsilon_{i,t} \quad i = 1, 2, ..., m, t = 1, 2, ..., n \tag{3.2}$$

where α, β and δ are the parameters to be estimated. The dependent variable $\pi_{i,t}$ is the current return on asset of average firms for country i at time t.

Consider an error structure of the form $\epsilon_{i,t} = \nu_i + e_{i,t}$, with $\nu_i \sim i.i.d.N(0, \sigma_\nu^2)$ and $e_{i,t} \sim i.i.d.N(0, \sigma_e^2)$ which are independent from error $E(e_{i,t}, e_{k,s}) = 0$ if $t \neq s$ or $i \neq k$ and $E(\nu_i, \nu_k) = 0$ if $i \neq k$. The

[3]It should be noted that dependent and independent variables for firms within each country are averaged for every year between 2003 and 2012 in order to obtain a two dimension panel and therefore 170 observation are produced.

[4]All panel models are dynamic as they exploit the longitudinal nature of panel data. However, there is a distinction within the literature between "static" and "dynamic" panel data models. Dynamic models include a lagged dependent variable on the right-hand side of the equation. Nevertheless, lagged π is effectively an endogenous explanatory variable in equation (3.2) with respect to both e_{it} and ν_i, therefore OLS regression assumptions are not met and GMM is an unbiased and consistent estimator.

term ν_i captures unobserved heterogeneity in country profitability. It can be interpreted as a collection of factors that are specific to country i but unobserved and e_{it} is an idiosyncratic error that accounts for the proportion of firm profit that correlate neither across time nor across countries. The equation above is estimated using random and fixed effect models and the tables containing results are shown in the result section, however, since those estimations yields inconsistent parameters, the GMM technique is used to overcome such inconsistencies in the estimated parameters.

3.5 Description of the data

In this study, financial soundness is tested grouped in liquidity and efficiency ratios, the macro-economic environment measured by GDP growth and inflation and in the special context of economies in transition, privatised environment have a role in defining the performance behaviours of firms. Return on assets (ROA) is defined as an index for firm performance and it is considered to be a dependent variable. ROA is a ratio of a firm's net income divided by its total assets. This provides an indication of the way in which management employ their assets to generate sufficient earnings, whether or not the performance of firms appear to be improving or deteriorating when compared with competitors. These matters can be better understood by analysing this ratio. This ratio is generally defined in percentage terms, and a higher ratio indicates improved performance. This ratio and Return on Equity (ROE)[5] are used in literature as indexes for the performance of firms.

3.5.1 Data sample of firms from Central and Eastern Europe

The overall data set comprises of a pooled cross section, where the same sample of companies are included each year. The data is widely

[5]ROE is a straightforward ratio that measures a company's return on its investment by shareholders.

perceived to representative and covers of very large companies [6] from almost all segments in Central and East European countries for the period 2003-2012 covering the post-privatisation period. The data set includes approximately 12,000 firms representing the dominant members of their respective industries which covers a variety of business types as shown in Table 3.4. The largest groups of companies, in terms of numbers, are, as expected, the manufacturing companies, wholesale/retail trade companies and construction companies.

As per the dispersion of data amongst counties, as shown in the Table 3.5, Poland, Ukraine, Serbia and Romania have the most companies and Estonia, Slovenia and Lativa have the least number in the sample.

The main source of data obtained is from the Amadeus database. The database covers the financial data of companies from the selected 17 European countries of Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Liechtenstein, Lithuania, Macedonia, Moldova, Montenegro, Serbia, Slovakia, Slovenia, Poland and Ukraine, which all are countries with economies in transition and members of the European Bank for Reconstruction and Development (EBRD). The data set is supplemented with macro-economic data obtained from the World Bank statistics data set and privatisation factors obtained from the EBRD database. The variables for companies in each country over the years have been averaged in order to use the two-dimension panel and therefore, 170 observations have been

[6] Amadeus database categorises companies in terms of annual turnover, total assets or total number of employees for the last available year. **Very large companies** that match at least one of the following criteria:

- Operating Revenue $\geq$ 100 million EUR (130 million USD)
- Total assets $\geq$ 200 million EUR (260 million USD)
- Employees $\geq$ 1,000
- Listed

Notes: Companies with ratios operating revenue per employee or total assets per employee of below EURO 100 Million (USD 130 Million) are excluded from this category. Companies for which operating revenue, total assets and employees are unknown but have a level of capital over 5 million EUR (6.5 million USD) are also included in the category.

Type of Business	
Accommodation and food service activitie	346
Administrative and support service activ	310
Agriculture, forestry and fishing	294
Arts, entertainment and recreation	61
Construction	828
Education	259
Electricity, gas, steam and air conditio	443
Financial and insurance activities	528
Human health and social work activities	315
Information and communication	349
Manufacturing	3,667
Mining and quarrying	380
Other service activities	44
Professional, scientific and technical a	444
Public administration and defence; compu	354
Real estate activities	373
Transportation and storage	693
Water supply; sewerage, waste management	151
Wholesale and retail trade; repair of mo	2,021
Total	**11,860**

Table 3.4: Sample breakdown by type of business

produced.

The dependent and independent variables are constructed from financial statements of companies (balance sheet and income statement). Amadeus database provides details of the financial statements, as well as of main financial ratios. ROA is selected as the dependent variable and for independent variables; there are three groups of firm specific, macro-economic and privatisation variables.

3.5.2 Descriptive statistics

Based on literature review, ROA as the profitability measure is selected. Also used is ROE as an alternative measure of profitability for robustness. Since data characteristic of the latter measure are simi-

	Country	Number of Firms
1	BOSNIA AND HERZE	965
2	BULGARIA	596
3	CROATIA	312
4	CZECH REPUBLIC	761
5	ESTONIA	69
6	HUNGARY	455
7	LATVIA	98
8	LITHUANIA	151
9	MACEDONIA	253
10	MOLDOVA REPUBLIC	656
11	MONTENEGRO	220
12	POLAND	2,027
13	ROMANIA	1,314
14	SERBIA	1,548
15	SLOVAKIA	438
16	SLOVENIA	82
17	UKRAINE	2,108
	Total	**12,053**

Table 3.5: Sample breakdown by country

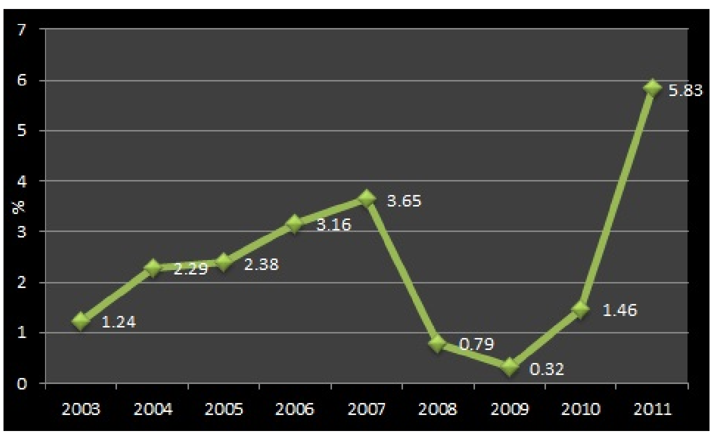


Figure 3.1: Profitability (ROA) mean trend

lar to that of ROA, this section only reports descriptive statistics for ROA.

Figure 3.1 and Table 3.6 show the trend of profitability over the

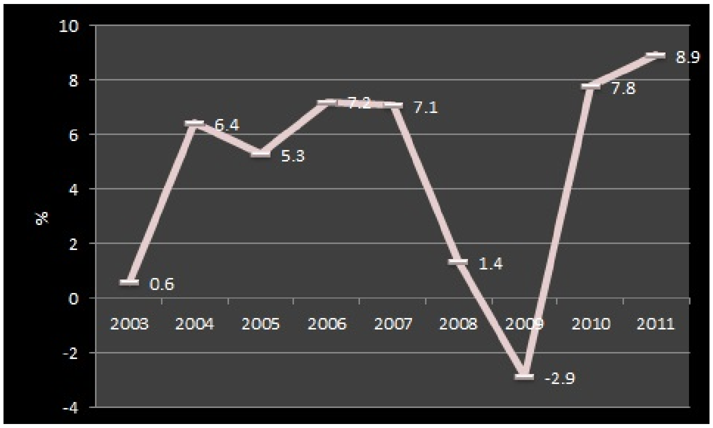


Figure 3.2: Profitability (ROE) mean trend

Figure 3.3: Stock market capitalisation trend

10 years reviewed. During this period, the return of companies on assets had shown improvement until 2007, after which a decreasing trend is observed until 2009 due to the global financial crisis. From 2009 onwards, an increasing trend was noted which reached its peak of 5.83% for ROA and 8.9% for ROE. This was higher than peaks observed before the crises in 2007 (3.65% and 7.10% for ROA and ROE, respectively). Moreover, Figure 3.5 also shows a similar trend for individual countries. The countries more-or-less experienced the same pattern; a decreasing trend occasionally between 2007 and 2009

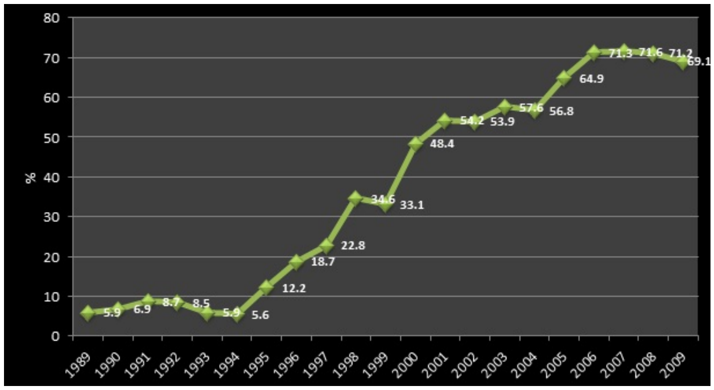


Figure 3.4: Asset share of foreign owned banks

and the recovery started 2010 onward. More specifically, companies in countries such as Bosnia, Bulgaria, Estonia, Lithuania, Macedonia, Moldova, Montenegro, Romania, Serbia, Slovakia, Slovenia and Ukraine experienced bottom profitability in 2009 and the recovery commenced immediately in 2010. However, companies in other groups of countries such as Croatia and Hungary experienced a decrease in profitability until 2010 and 2011, respectively. The companies located in the remaining three countries of Czech Republic, Latvia and Poland had experienced bottom profitability in 2008 and started recovery immediately. Therefore, it implies that in some countries the impact of crises was immediate (countries, which show bottom profitability in 2008) while in some others, the impact occurred with delay (countries with bottom profitability in 2009 and 2010).

As our data set include one episode of structural break which is 2007 financial crises, as discussed in full detail in previous chapter, any failure to take into account the potential presence of structural breaks can lead to misleading inference in time series regarding the order of integration. However as discussed in full details in Appendix D.1, none of the existing unit root test which at the same time take care of structural breaks are not applicable for the case of our data as the employed panel data needs to have at least 10 years of complete data and strongly balanced. Therefore the investigation of designing proper unit root test which at the same time takes care of structural break in an unbalanced panel is left to future research.

	Mean	Min	Max	SD
2003	1.2	-4.4	9.4	3.5
2004	2.3	-4.6	9.7	3.8
2005	2.4	-4.4	7.5	3.3
2006	3.2	-3.4	9.4	3.3
2007	3.6	-3.3	9.8	3.5
2008	0.8	-10.0	7.7	4.0
2009	0.3	-4.1	5.1	2.7
2010	1.5	-3.5	7.6	3.4
2011	5.8	1.1	22.7	7.1

Table 3.6: Profitability (ROA) statistics trend

In this analysis, a variety of variables will be investigated which could logically affect ROA from a theoretical perspective. The sample is tested for multi collinearity and this revealed no problem during analysis. Moreover, independent variables are reported as a percentage, except for sales/NWC and interest coverage ratios which are reported as times. Credit period is reported in number of days. The simple statistics are shown in Table 3.7.

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA (%)	144	2.13	3.90	-10.05	22.75
Costs of Employees/Operating Revenue (%)	124	25.98	12.18	4.51	68.88
GDP Growth (%)	127	5.43	9.19	-18.00	46.00
Inflation, GDP Deflator (%)	128	6.84	5.89	-4.00	29.00
Credit Period (Days)	133	67	41	0	183
Sales /Net Working Capital (x)	133	12	33	-19	381
EBIT/Interestpaid (x)	96	8.81	6.19	1.39	39.66
Stock Market Capitalization (%)	103	27.87	24.92	0.00	181.20
Asset share of foreign-owned banks (%)	111	70.11	25.69	12.10	99.40

Table 3.7: Statistics of variables used

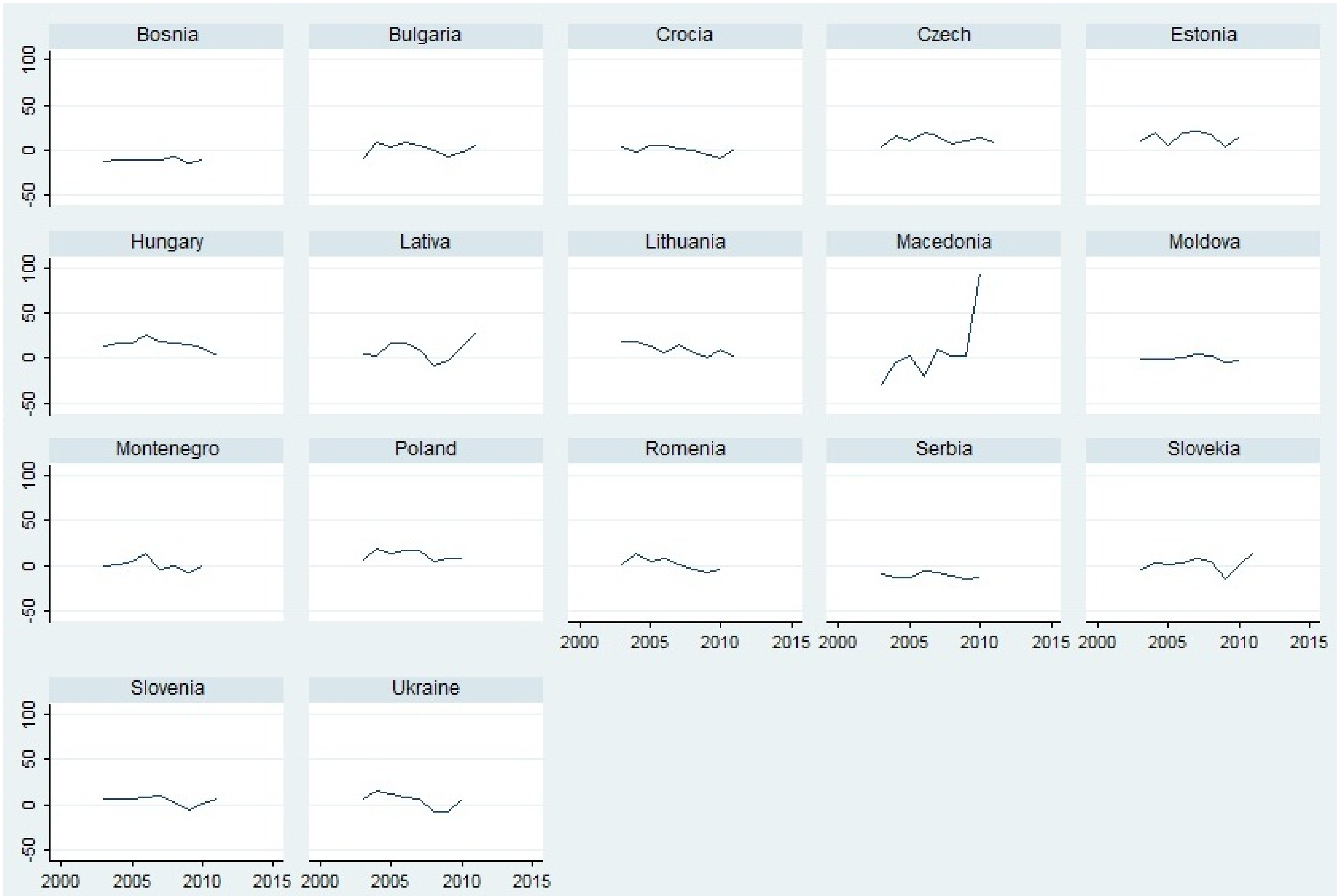


Figure 3.5: Profitability mean trend for each country

3.6 Results

3.6.1 Estimation results

In Table 3.2 the employed variables along with their expected impact on the performance of have been listed. This study uses a balanced panel of 17 Central and Eastern European very large companies spanning the period between 2003 and 2012. Equation (3.2) forms the basis of the estimation. In static relationships, the literature usually applies least squares methods on Fixed or Random Effects models. However, in dynamic relationships, these methods produce biased (especially as the time dimension T becomes smaller and cross sections become bigger) and inconsistent estimates (see (Nickell, 1981)). The econometric analysis of model (3.2) involves the following issues: First, stationary of the panel -using a unit root is tested for balanced panels- and confirming weak correlation between descriptive variables (see Tables 3.10 and Table 3.14). Secondly, whether individual effects are fixed or random are examined. In addition, techniques for dynamic panel estimation are used. Finally, the estimates are tested for robustness.

The use of a relatively large T in a model for the profitability of firms may be criticised on grounds of non-stationary of the panel. Maddala and Wu (1999) suggest the use of the Fisher test, which is based on combining the p-values of the test-statistic for a unit root for each country. They state that not only does this test perform better compared to other tests for unit roots in panel data, but it also has the advantage of not requiring a balanced panel, as most tests do. The results of this test are presented in Table 3.10. The null hypothesis of non-stationary is rejected at the 5% level for all variables except for stock market capitalisation and working capital turnover. The estimation of the model continues by including a first difference of these variables. The second issue is the choice between a fixed effect (FE) and a random effects (RE) model. These results can be seen in Table 3.11 and Table 3.12. As seen most of the variables, signs do not appear to be logical according to theory and are not considered significant. As indicated by Hausman (1978) (see Table 3.13), the difference in coefficients between FE and RE is systematic, providing evidence in favour of a FE model.

However, as mentioned above, the least squares estimator of the FE model, in the presence of a lagged dependent variable amongst the regressors, is both biased and inconsistent. The first attempt to solve the problem of bias and inconsistency in dynamic models was made by Anderson and Hsiao (1982), who suggested the use of an instrumental variables estimator based on the first-differenced form of the original equation. Arellano and Bond (1991) observe that the Anderson-Hsiao estimator lacks efficiency, as since it does not employ all the available instruments. They suggest that efficiency gains can be obtained by employing all available lagged values of the dependent variable and lagged values of exogenous regressors as instruments. Nevertheless, the Arellano and Bond estimators have been criticised when applied to panels with small T, the argument being that under such conditions this estimator is not efficient if weak instruments are employed.

Equation (3.2), dynamic in nature, prevents the use of the standard ordinary least squares (OLS) estimator, which will be biased and inconsistent due to the correlation between the unobserved panel-level effects and the lagged dependent variable. Therefore the Arellano and Bond (1991) two-step General Method of Moments (GMM) approach can be employed to solve the errors and biases (see also (Roodman, 2006)). With many panels and few periods, and under the assumption of no correlation in the idiosyncratic errors, this estimator removes the panel-specific heterogeneity by first differencing the regression equation. The results of the dynamic model making use of General Method of Moment (GMM) are presented in Table 3.8 which provides evidence on the impact of several firm-specific and macro-economic characteristics and privatisation impact on firm profitability[7]. The Table displays the relevant variables and shows how they perform in the model along with the parameter estimates for the variables, their standard errors and level of significance. In general, most variables were found to be significant (less than 5

Moreover, the Sargan (1958) test for over-identifying restrictions fails to reject the null hypothesis that instruments are valid. There-

[7] It should be noted that after running multiple models, variables that were not significant were removed from the model equations. These included variables of firm's debt to equity and inventory turnover ratios.

fore, presents evidence that the underlying over identifying restrictions are valid. The Arellano-Bond test for serial correlation in the first-differenced residuals presents no evidence of model misspecification. It is important to note that when the idiosyncratic errors are independently and identically distributed, the first-differenced errors are first-order serially correlated, and the test rejects the null hypothesis of zero autocorrelation in the first differenced errors at order one. The value test for the second order autocorrelation, however, implies that the moment conditions of the model are valid.

The magnitude and significance of the coefficient on the lagged ROA confirm the dynamic nature of the model, and shows a moderate persistence in return. The coefficient estimate of 0.54 suggests that the profits tend to adjust fairly quickly to their average level. As explained by Stierwald (2010) high earnings in the past, provides the opportunity to realise high profits in the future. The greater the value, the more successful the firm has been in maintaining its competitive position. Firms can benefit from previous profits if, for instance, retained earnings are employed in operation or re-invested into research and development (Hirschey and Wichern, 1984). Therefore, the positive and significant coefficient for one-year lagged ROA confirms the positive conditional serial correlation in returns that was found in this research's model. This result is consistent with those reported by Stierwald (2010) and Demir (2009).

Therefore the investigation of designing proper unit root test which consider more than one break in a unbalanced panel of long span is left for future research to take care of all these issues simultaneously.

For chapter three, Im-Pesaran-Shin test ic conducted, however, z statistics could not be calculated as normality of Z-t-tilde-bar requires at least 10 observations per panel with unbalanced data.

Credit payable, which provides a sense of a company's liquidity, indicates the average number of days a company takes to pay its suppliers. The greater this number, the more cash the company has for other working capital needs and as expected positively affects the profitability. This result goes against the findings reported by Raheman and Nasr (2007) where they argued that the negative relationship between accounts payable and profitability is due to the fact that less profitable firms wait longer to pay their bills. Although, the more the company's managers are able to convince their creditors to pay them in longer periods, they would have greater liquidity for their day to day transactions, which leads to more profitability.

Referring to the impact of efficiency ratios, sales to net working capital ratio is expected to positively affect the profitability and the estimation shows the same. This ratio measures the number of times working capital turns over annually in relation to net sales. This result is in line with the result reported by Sutanto and Pribadi (2012).

Cost management as the other side of corporate efficiency is important since over employed firms would have higher employee expenses compared to the operating profit of companies. Therefore, it leads to less profit for the company.

As expected, interest coverage ratio has positive impact on firm's profitability, since the greater this ratio is, the more the interest before interest and tax is compared to the financial expense the company is required to pay. Thus, indicating that the company has sound profitability before deducting payable taxes. This is also reported by Moody's rating agency that corporations are vulnerable to bank funding, short-term borrowing and floating interest rates, which all are impacts financing expenses, which decrease this ratio.

Inflation (GDP deflator) as a macro-economic factor as it was expected negatively affects the performance of firms. This is similar to the finding of Prasetyantoko (1997) . This implies that companies' management is not fully able to forecast future inflation such as possible increase in raw materials prices. Thus, they are not properly hedged or have not been appropriately adjusted to achieve higher profits. As reported by Demir (2009), inflation uncertainty significantly lowers industrial output growth. The study found a significant negative impact of macro-economic uncertainty measured by real exchange rate, inflation uncertainty and country risk on net profits of manufacturing firms.

Impact of GDP growth on profitability, as expected, has a positive and significant effect, confirming the results of studies undertaken by Muia (2009) and McNamara and Duncan (1995). Muia (2009) found that the relation between GDP growth and growth of firms through mergers and acquisitions is positive when firms seek immediate increases in production capacity in a growing economy, however, the desire for firm to grow through a merger or an acquisition might in turn be tempered by unfavourable business conditions. Overall, it is suggested that the empirical evidence on the relationship between GDP growth and growth of firms through mergers and acquisitions is limited and mixed. Similarly, McNamara and Duncan (1995) found that increase in the level of economic activity, as measured by GDP is accompanied by increases in ROA, confirming that increase in notions' economic activity flows into sales activity and thus positively affect ROA.

As one of the major factor showing succeeding in privatisation is stock market development, stock market capitalisation as percent of GDP as its index was chosen. As it can be seen in Figure 3.3, between the years from 1989 and 2006, this figure shows an increasing trend when the "big" financial crises happened. From 2008, it has started increasing; however, it did not reach its peak in 2006. This factor in the regression analysis has a positive effect confirming the positive impact of stock market expansions on the firm's performance. This result is in line with the study of Boubakria et al. (2002) where they report that "corporate governance and the economic environment have a significant impact on the extent of performance changes: for instance a lower level of political risk, a friendly institutional environment, more developed stock markets and a higher foreign ownership are significantly related to improvements in performance." This is in addition to Moody's analysis where they found the depth of domestic capital market as one of the key factor to affect the risk profile of corporations in a positive way.

Fiscal decentralisation cannot be successful in isolation unless it is joint with the reforms of a banking system. The study employed a variable of asset share of foreign owned bank to measure for privatisation and as expected it shows a positive impact on the firm's performance during the privatisation period. This is implying that the more the banking reforms take place, banking supervision is improving more and also the prudential regulations improve, which leads to being more open for foreign banks to enter to the local market and enjoy the competitive banking environment. Moreover, this leads to more lending to the private sector and ultimately increases the privatised firms performance. The result is in line with the findings of

Crivelli (2012) where it was found that there was a negative impact of banking reform on the cyclically-adjusted local government budget balance (In percentage of GDP) implying that the less banking reform the more the government need to assign budget for the economy. This result is also in line with the Moody's results where they found the strength of banking system as main factor affecting the corporations risk profile.

Impact of privatisation on companies' performance is linked with privatisation method being used dominantly. In this regard after including the dummy variable for method of privatisation with three categories of privatisation through sale, MEBO and mass privatisation (Voucher method), it was noticed that privatisation via sale of assets has a positive and stronger impact compared to the other methods on the firms profitability for both ROA and ROE. The research shows this impact by monitoring the countries that used this method of privatisation, which all has higher profitability over the period under review. These results are shown in Table 3.15. These empirical results also are supported by the unsuccessful story of Ukraine where Voucher method of privatisation was employed. Galyna and Stefan (2004) also confirms the negative impact of voucher method on firms performance since it led to de-motivated insider managers.

Moreover, this study included the interaction of economic growth and method of privatisation on the performance of firms. The results show that impact of economic growth on firms' profitability is stronger in countries where sale of asset as the dominant method of privatization were used compared to the countries used mass privatization. Therefore, as hypothesised, the countries that had used the sale method of privatisation had companies' performance increase with faster pace than the countries that employed the voucher method. This result is in line with the study undertaken by Bennett et al. (2007).

3.6.2 Robustness checks: alternative measure of firm profitability

A robust check was undertaken to confirm the reliability of the results. Two checks were undertaken by re-estimating the coefficients and the results are reported in Table 3.9. The robustness checks were carried out using Return on Equity as the dependent variables (Figure 3.2 shows its trend). The results do not differ from those obtained previously, which confirms that the efficiency, liquidity macroeconomic and privatisation factors are the driving factors in the performance of firms and of very large companies in most European economies.

In addition, if the same regression is undertaken for more European countries, other than the Central and Eastern European countries in transition phase, similar results are produced. These are illustrated in Table B.1. Moreover, the trend for ROA is similar to the trend inselected CIS countries (see Figure B.1 and Figure B.2). Same variables were employed in the regression model. Similar results were achieved in terms of significance impact of variables and size of coefficient, implying that the behaviour of the profitability of firms in most European countries is similar.

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ROA(-1)	0.542111	0.158899	3.41	0.001	0.2306743	0.8535468
Cost of Employee/Operating Revenue (%)	-0.02835	0.016847	-1.68	0.092	-0.0613726	0.0046661
GDP Growth (Annula %)	0.150289	0.050826	2.96	0.003	0.0506714	0.2499056
Inflation, GDP deflator (Annual %)	-0.02855	0.022189	-1.29	0.198	-0.072035	0.014944
Credit Period (days)	0.005361	0.003025	1.77	0.076	-0.0005678	0.0112894
d.Sales/Net Working Capital (x)	0.003522	0.001139	3.09	0.002	0.0012895	0.0057544
EBIT/Interest Paid (%)	0.087941	0.04065	2.16	0.031	0.0082683	0.1676134
d.Stock market capitalisation (in per cent of GDP)	0.045604	0.007312	6.24	0	0.0312716	0.0599358
Asset share of Foreig-owned banks (in per cent)	0.032417	0.01435	2.26	0.024	0.0042904	0.0605428

Number of instruments = 23

Wald test

chi2(9)	=3427.89	
Prob > chi2	=0	
Arellano-Bond test for zero autocorrelation in first-differenced errors		
Order	**z**	**Prob>z**
1	-1.6667	0.0956
H0:no autocorrelation		
Sargan test for overidentifying restrictions		
chi2(20)	= 5.374059	
Prob > chi2	= 0.9799	
H0: overidentifying restrictions are valid		

Table 3.8: ROA determinants; employing General Method of Moment

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ROE(-1)	-0.03041	0.161327	-0.19	0.851	-0.3466005	0.2857894
Cost of Employee/Operating Revenue (%)	-0.12662	0.094396	-1.34	0.18	-0.3116363	0.0583873
GDP Growth (Annula %)	0.98403	0.138648	7.1	0	0.7122853	1.255774
Inflation, GDP deflator (Annual %)	-0.2435	0.15767	-1.54	0.123	-0.5525275	0.0655277
Credit Period (days)	0.049551	0.019738	2.51	0.012	0.0108656	0.0882371
EBIT/Interest Paid (%)	0.109794	0.048078	2.28	0.022	0.0155634	0.2040242
Stock market capitalisation (in per cent of GDP)	0.053183	0.005861	9.07	0	0.0416957	0.0646698
Asset share of Foreig-owned banks (in per cent)	0.061083	0.067538	0.9	0.366	-0.0712896	0.1934549
Constant	-11.8697	8.162061	-1.45	0.146	-27.86704	4.127647
Number of instruments = 23						
Wald test						
chi2(9)	=2035.26					
Prob > chi2	=0					
Arellano-Bond test for zero autocorrelation in first-differenced errors						
Order	**z**	**Prob>z**				
1	-0.25474	0.7989				
H0:no autocorrelation						
Sargan test for overidentifying restrictions						
chi2(20)	=7.430932					
Prob > chi2	= 0.9168					
H0: overidentifying restrictions are valid						

Table 3.9: Robustness check

		ROA		GDP Growth (Annual %)		Inflaiton, GDP deflator (Annual %)	
Maddala-Wu panel unit root test		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse chi-squared(46)	P	58.9717	0.005	169.0446	0	94.8423	0
Inverse normal	Z	-1.5726	0.0579	-4.5646	0	-3.6719	0.0001
Inverse logit t(119)	L*	-2.1021	0.0192	-8.8425	0	-4.863	0
Modified inv. chi-squared	Pm	3.0283	0.0012	17.1306	0	7.8553	0

		Sales/Net Working Capital		Asset share of foreign-owned banks (in per cent)		EBIT/Interestpaid	
Maddala-Wu panel unit root test		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse chi-squared(46)	P	3.01625	0.55	314	0	36.871	0.0244
Inverse normal	Z	-0.3005	0.3819	-8.7866	0	-1.626	0.0252
Inverse logit t(119)	L*	-0.2829	0.389	-20.4912	0	-1.8469	0.0349
Modified inv. chi-squared	Pm	-0.2297	0.5908	35.3244	0	2.2419	0.0125

		Stock market capitalisation (in per cent of GDP)		Credit Period		Cost of Employee/Operating Revenue	
Maddala-Wu panel unit root test		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse chi-squared(46)	P	26.2582	0.6619	127.5539	0	187.8242	0
Inverse normal	Z	-0.1919	0.4239	-2.7058	0.0034	-6.7501	0
Inverse logit t(119)	L*	-0.1438	0.443	-6.9291	0	-12.5175	0
Modified inv. chi-squared	Pm	-0.4831	0.6855	11.9442	0	21.3574	0

Table 3.10: Maddala-Wu panel unit root test

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ROA(-1)	0.279159	0.130537	2.14	0.04	0.0138762	0.5444415
Cost of Employee/Operating Revenue (%)	0.002911	0.021068	0.14	0.891	-0.0399031	0.0457255
GDP Growth (Annula %)	0.138598	0.033646	4.12	0	0.0702207	0.2069749
Inflation, GDP deflator (Annual %)	0.00043	0.052349	0.01	0.993	-0.1059557	0.1068162
Credit Period (days)	0.002912	0.007145	0.41	0.686	-0.0116071	0.0174315
Sales/Net Working Capital (x)	-0.00073	0.003566	-0.21	0.838	-0.0079806	0.0065142
EBIT/Interest Paid (%)	0.113815	0.069012	1.65	0.108	-0.0264331	0.2540633
Stock market capitalisation (in per cent of GDP)	0.035037	0.01068	3.28	0.002	0.0133334	0.0567414
Asset share of Foreig-owned banks (in per cent)	0.030808	0.020941	1.47	0.15	-0.0117484	0.073365
_cons	-3.17706	1.769345	-1.8	0.081	-6.772803	0.4186796

Fixed-effects (within) regression	Number of obs = 54
Group variable: var1	Number of groups = 11
R-sq: within = 0.6609	Obs per group: min = 2
between = 0.2239	avg = 4.9
overall = 0.3153	max = 6
	F(9,34) = 7.36
corr(u_i, Xb) = -0.1886	Prob > F = 0.0000

F test that all u_i=0: F(10, 34) = 3.69 Prob > F = 0.0020

Table 3.11: FE estimation

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ROA(-1)	0.631962	0.09908	6.38	0	0.4377693	0.8261538
Cost of Employee/Operating Revenue (%)	0.008457	0.019154	0.44	0.659	-0.0290838	0.0459974
GDP Growth (Annula %)	0.054143	0.021356	2.54	0.011	0.0122869	0.0959993
Inflation, GDP deflator (Annual %)	-0.00679	0.043277	-0.16	0.875	-0.0916145	0.0780269
Credit Period (days)	-0.00926	0.00612	-1.51	0.13	-0.0212537	0.0027345
Sales/Net Working Capital (x)	0.000403	0.003808	0.11	0.916	-0.0070594	0.0078658
EBIT/Interest Paid (%)	0.129121	0.059959	2.15	0.031	0.011603	0.2466394
Stock market capitalisation (in per cent of GDP)	0.044067	0.012083	3.65	0	0.0203838	0.0677491
Asset share of Foreig-owned banks (in per cent)	-0.00137	0.012542	-0.11	0.913	-0.0259502	0.0232142
_cons	-0.3563	1.370934	-0.26	0.795	-3.043278	2.330686

Random-effects GLS regression	Number of obs = 54
Group variable: var1	Number of groups = 11
R-sq: within =0.5109	Obs per group: min = 2
between =0.9165	avg = 4.9
overall = 0.8413	max = 6
	F(9,34) = 132.39
corr(u_i, Xb) = 0 (assumed)	Prob > F = 0.0000

Table 3.12: RE estimation

	---- Coefficients ----			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	FE	RE	Difference	S.E.
ROA(-1)	0.2791589	0.6319615	-0.3528027	0.0849889
Cost of Employee/Operating Revenue (%)	0.0029112	0.0084568	-0.0055456	0.0087735
GDP Growth (Annula %)	0.1385978	0.0541431	0.0844547	0.026
Inflation, GDP deflator (Annual %)	0.0004302	-0.0067938	0.007224	0.0294542
Credit Period (days)	0.0029122	-0.0092596	0.0121718	0.0036871
Sales/Net Working Capital (x)	-0.0007332	0.0004032	-0.0011364	.
EBIT/Interest Paid (%)	0.1138151	0.1291212	-0.0153061	0.0341682
Stock market capitalisation (in per cent of GDP)	0.0350374	0.0440665	-0.0090291	.
Asset share of Foreig-owned banks (in per cent)	0.0308083	-0.001368	0.0321763	0.0167693

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 45.59
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Table 3.13: Hausman test

	Cost of Employee/ Operating Revenue (%)	GDP Growth (Annula %)	Inflation, GDP deflator (Annual %)	Credit Period (days)	Sales/Net Working Capital (x)	EBIT/Interest Paid (%)	Stock market capitalisation (in per cent of GDP)	Asset share of Foreig-owned banks (in per cent)
Cost of Employee/Operating Revenue (%)	1							
GDP Growth (Annula %)	-0.1466	1						
Inflation, GDP deflator (Annual %)	0.2612	0.1768	1					
Credit Period (days)	0.1417	-0.0124	-0.0649	1				
Sales/Net Working Capital (x)	0.164	0.0125	0.0609	-0.2104	1			
EBIT/Interest Paid (%)	-0.1178	-0.0269	-0.2723	-0.194	0.0718	1		
Stock market capitalisation (in per cent of GDP)	0.1468	0.0927	-0.0868	0.0297	0.0285	0.0556	1	
Asset share of Foreig-owned banks (in per cent)	-0.3497	0.1127	-0.5686	0.1639	-0.0406	0.1166	-0.0672	1

Table 3.14: Correlation matrix of variables

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Method of Privatization (Sale of Assets)	3.705207	0.8623495	4.3	0	1.997958	5.412455
Method of Privatization (Voucher,Mass Privatization)	1.579058	0.852354	1.85	0.066	-0.1084012	3.266518
Interaction between GDP Growth and Method of Privatization (Sale of asset)	0.1116153	0.140535	0.79	0.429	-0.1666107	0.3898414
Interaction between GDP Growth and Method of Privatization (Voucher)	-0.00000964	0.1213061	0	1	-0.240167	0.2401477
Constant	0.0294825	0.6422544	0.05	0.963	-1.242029	1.300995

Source	SS	df	MS	
Model	389.85	5	77.97	Number of of Observation =127
Residual	1214.34	121	10.03	F(5, 121) = 7.77
Total	1604.2	126	12.731	Prob > F =0
				R-squared = 0.2430
				Adj R-square d = 0.2117
				Root MSE = 3.168

Table 3.15: Regression employing dummy variables, ROA as dependent Variable

3.7 Discussion and conclusions

This study applies a new method to investigate the relative importance of specific firm effects and macro-economic effects using financial ratios grouped as leverage, liquidity, efficiency, macro-economic factors and privatisation indexes on performance of companies employing a dynamic two dimension panel model. A continuous variable model is used, as an alternative to the more conventional ANOVA to examine accounting-based financial ratios and macro-economic variables. A sizable corporate and macro-economic effect on business performance was thereafter found. These results are only valid for significantly large corporations in European countries and therefore, may not be generalised for other samples.

The analysis answers the three questions that motivated this research. First, it was found that the probability of firms to be profitable is linked to the manner in which they allocate scarce resources. Secondly, macro-economic and the privatised environment plays an important role in determining the prospective profitability of economic units. Finally, the study shows that the macro-economic impact appears to be qualitatively and quantitatively different for each nation, pointing to the importance of inclusion of macro-economic factors.

It was hypothesised that highly liquidated, less leveraged firms are more profitable than less liquid, and highly leveraged ones. The estimated result confirms this hypothesis.

Macro-economic policies are important. Inflation may increases the sales revenues through increasing the product prices, which will result in higher profitability just in case the company managers make wise decisions to adjust the prices according to expected inflation, otherwise, a negative impact of inflation on firms profitability can be expected. The case in the research presented a negative impact, implying the inability of the firms to suitably forecast the inflation. A secondary hypothesis was as follows: countries that used the voucher method of privatisation would have lower performance in firms. This was confirmed with the empirical results as even in the post-privatisation period still they experienced lower profitability compared with other companies in countries where other privatisation methods are used.

This study is not free from limitations. It used limited numbers of financial ratios and for selected countries only. For future studies, there is a need to cover more countries, use data for the other groups of companies in terms of size of firms other than for very large companies employed in this study and for a longer period. Moreover, for more accurate results, the three dimension panel analysis could be used in order to detect the companies and countries effect at the same time[8]. To summarise, this study provides new estimates of the influence of macro-economic and firm specific factors on business performance in a dynamic setting.

The estimated results are relevant to policy as it shows the firms ROA as significantly persistent with one lag, which implies that the manager of firms are able to predict next year's performance while being aware of the current year's performance. In addition, corporate managers may predict that with each increase in the employees' expenses to operating revenue, which is due to recruiting more employees or decreasing in operating revenue, the ROA will be affected by almost 3%. As mentioned, liquid the firm is the more they can response to market changes. Such as in case of sudden decrease in raw material prices, firms with liquidity in their hand can benefit from such opportunity and increase their profit margin, while firms with less liquidity may lose such opportunity. Credit period (payable period) is one of the liquidity indexes and in the model shows itself with positive impact on profitability, which implies that a competent corporate managers need to consider liquidity at any time.

At a macro level, macro-economic policy makers need to take into account macro-economic factors carefully. Any adverse movement in such factors may result in decrease in profitability. As such, one can refer to main macroeconomic factors such as GDP growth rate -which shows heavy impact on firms profitability-, inflation and more specifically level of market capitalisation -which means level of development in capital markets- and creating competition in banking sector which implied from existence of foreign banks in banking industry and ease of entering to the banking industry. This is all shown to have signifi-

[8]In fact our data originally has got three dimension but in order to simplify the results the data was averaged for all the companies in each country and for each year

cant impact on a firms' performance. The latter two factors show the level of privatisation in the economy. Therefore, implying that economic privatisation improves the economic performance of each firm operating in privatised economies than economies with a heavy public sector presence.

Chapter 4

Scoring/rating firms and financial institutions using fuzzy logic systems and data mining techniques

4.1 Introduction

Nowadays, one of the primary reasons, which prevent investors from entering into emerging markets, is the uncertainty of these markets. This is because of globalisation, which has led to emergence of such complex network relationship in business environment. As financial market get more complicated, risk management becomes crucial for all types of financial institutions operating in such complicated environment. Moreover, the recent negative development in financial sector in US and a number of high profile bank failures in Asia[1] brought

[1] e.g. the Hokkaido Takushoku Bank, Ltd.; possibly the most notable failure of the Asian financial crisis, "Hokutaku" went bankrupt in 1997, almost 100 years after its inception as a "special bank" to promote development on the island of Hokkaido. The bank specialised in long term, low-interest loans and debt insurance that would help grow specific sectors on the island, like fishing and agriculture. In 1939, the government deregulated Hokutaku, allowing it to offer short-term financing and bank accounts. The bank grew and eventually became

attention to the importance of credit risk management. The decision whether or not to stop offering loans is a complex process and involves uncertainty and credit risk. The assessment of the loan proposal requires expertise, experience and a systematic approach.

Numerous rating institutions provide risk assessments for corporate companies as well as for financial institutions, as such rating institutions one may refer to big rating agencies such as Moody's, Fitch Rating, Standard and poor's, capital intelligence and etc. However, unfortunately not all the corporations and financial institutions are rated by such rating institutions. Therefore, there is a need for in-house tailor made scoring/rating models to overcome this existing gap to calculate the risk associated with unrated credit proposals and make the comparison. This is not only the requirements of lenders, but also is required by supervisory authorities (see Appendix A.2) to enable them to assess the level of soundness in the banking sector that they supervise.

Another issue is related to the purchase of ready-made credit scoring/rating models instead of building one. Of course buying a ready-made customer credit scoring/rating models is recommended and a better choice for retail banks. Because the scoring/rating model, providers such as rating agencies have access to the large database of retail customers and their past credit default, it makes their rating models more accurate.

However, when referred to multilateral lenders (Multilateral banks such as regional (Asian Development Bank, African Development Bank) and sub-regional banks (East African Development bank and Black Sea Development Bank) who finance companies and different types of financial insinuations such as commercial banks, leasing companies in different countries, which normally are not rated, there is a need for developing an internal scoring/rating models in house. However, building scoring/rating models based on insufficient data[2], reduces the applicability of current statistical models such as logistic regres-

involved in risky real estate investments during Japan's late-1980s real estate bubble. The rest, as said, "is history".

[2]MDBs normally have very low default history which are called low default portfolio. This is resulted from a very few number of defaulted financial institutions or very large corporations

sion (see (Odeh et al., 2010)), discriminant analysis or neuro-fuzzy (see application of neuro-fuzzy in bankruptcy predictions (Vlachos and Tolias, 2003), (Yildiz and Akkoc, 2010), (Buachoom and Kasemsan, 2011), (Odeh et al., 2010), (Magni et al., 2006) in decision support (Setlak, 2008), in evaluation (Thipparat, 2011), (Lin et al., 2004), in clustering and classification (Grabusts, 2002)) types of models where they require sufficient number of default cases data to train the model. In addition non parametric models such as neural network or neuro-fuzzy models are not preferred by bankers as they act as black boxes where the information such as the weight of each value drivers on the overall credit rating/scoring is not observable.

Other than the previously mentioned statistical models, there are other theoretical models based on Merton option pricing theory (as such it can be referred to *KMV* developed by Moody's, and Credit Underlying Securities Pricing *CUSP* developed by credit Swiss and *Credit Grades* developed by JPMorgan, see Martin (2007)) which all are ruled out because of the following reasons:

- Only applicable for public traded companies not for emerging markets where the stock markets are not that developed and not all the corporations and FIs are listed. Moreover, it is not applicable for MDBs where they finance the corporations and FIs, which are not be traded in the capital market,

- Difficult to construct the theoretical EDF (Exposure at Default) without assumption of normally distributed of asset,

- Requires a huge database for calculating the empirical EDFs. In case of the MDB, the numbers of credit customers are limited and the loan tickets are normally bigger than commercial or retail banks,

- It does not distinguish between the types of loans, collateral, seniority of loans and etc.

- Not suitable for loans more than maturity of two year, MDBs normally provide long term loans to justify their aim as development bank (see Sobreira (2008),

- According to the Merton approach default can be occur just in the maturity time of loans, (see Wael (2008), Tudela Merxe (2003) and Uwe (2003) for more details.)

Credit Risk Plus model developed by credit Swiss is also ruled out because of its underlying assumptions. Such assumptions are infinite number of customers in each band which may leads to the overestimation of risk in small segment. This assumption makes the model best suited for very large and homogenous portfolios (see Wael (2008), Saunders and Alen (2002) and Uwe (2003) for more details). Therefore, is not applicable for the small portfolios, which is the underlying characteristic of MDBs' credit portfolios.

Credit Metrics is one of the reduced-form models which was designed by J.P Morgan, this was also ruled out because of the following underlying reasons:

- One has to wait until the end of the year to assess whether the company has been migrated,
- Transitions follow stable Markov process, which implies no dependency of migration to the historical past periods,
- Unable to distinguish between customers in different industries and countries,
- Using the historical data base for publicity traded bonds which will be result to bias estimation because the nature of loan financing is different and normally loans are not traded,
- The credit spread and interest rates used in valuation are all deterministic while they are changing over time and suggested to keep stochastically.
- Based on mark-to market mode, not default mode.

Only in Credit Portfolio View published by Mackinsey and Company in 1997 and developed by Tom Wilson in 1989, considers the macro-economic environment on the borrowers default. This model considers the Macro Economic factors e.g. inflation rate, unemployment rate, GNP growth rate and exchange rates on the probability of default of customers. The main steps of this model include:

- Obtain a time series of macro-economic variables and default histories,
- Regressing the default rates on macroeconomic variables to identify systemic factor coefficients,
- Extrapolate forecasts of macroeconomic variables,
- Calculate default rates by regressing default on the forecast of macroeconomic conditions,
- Simulate default rates over different possible macro-economic states to trace the distribution of conditional default probabilities for each rating,

Obviously from this model steps, the default rates need to be known. However the MDBs credit portfolio is low default portfolios.

Therefore, employing other types of models seems more applicable. Referring to expert judgment models and fuzzy models, this study focuses on the latter. For MDBs, two things always need to be taken into account at the same time: one is economic development of their member countries and the other one is to secure themselves against any possible risks while they generate enough revenue to cover their costs. Credit rating of assets therefore helps in determining the risks associated with their customers, define proper credit risk based pricing while granting a loan and consequently ensure adequate loan loss provisions.

In probability theory the attribute expected always refers to an expectation or mean value, and this is also the case in risk management. The basic idea for expected loss is that with the known default probability (DP) of borrowers, the exposure at default (EAD) (which is the amount of loan given) as well as risk of transaction or loss given default (LGD) (which considers type of collateral[3], product type, seniority of claim and etc.), and how much would be the expected loss of single obligor (see (Uwe, 2003) and (Christian et al., 2003) for more detail). These three major components as shown in Figure 4.1 are the basis for the standard credit risk measurement. Therefore, expected loss or general provision follows the formula below:

[3]Not all types of collateral carry same value and risks

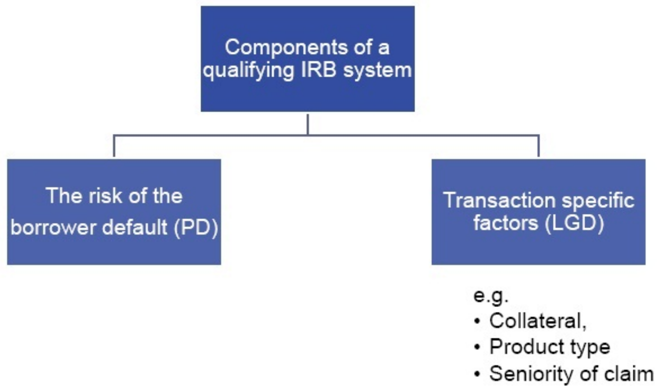


Figure 4.1: Borrower credit risk assessment components
Thun (2011)

$$General\ Provision(ExpectedLoss) = PD * LGD * EAD \qquad (4.1)$$

This article focuses on the first part, which is probability of default (PD). Most of the current credit scoring/rating models in order to come up with the probability of default, -ranges from simple ones such as Altman Z score. Logit and Probit regressions to the most complex ones such as neural networks (ANN) and genetic algorithm (GA) - ruled out because no data available to relate the input (credit worthiness attributes) to output (bankruptcy rate) and therefore train the model. Therefore, models that give an accurate picture of credit assessments based on minimal data are needed. One of such models is expert system, which is based on knowledge gained from previous experience. Fuzzy logic is an extension of expert systems that deals with reasoning that is approximate rather than precise.

Some benefits of fuzzy systems are; a) ability to model highly complex business problems as conventional expert systems failed to grow in business applications mainly due to the complex nature of many business problems, b)fuzzy systems are highly suited for modeling computationally complex non-linear problems which are poorly understood, c) efficient knowledge base, d) fuzzy rule based systems require fewer rules and execute faster than conventional rule based systems, e)a single rule applies by different degrees to a variety of situations, h) reduced model complexity and i) improved handling of uncertainty.

In designing a standard credit scoring/rating models based on fuzzy approach there are several standard major steps; a) identification of attributes affecting the credibility of the customer b) providing appropriate weights and c) development of a rule based inference engine and expert system.

The primary target and motivation of this study is to propose a credit scoring/rating model for financial institutions and very large corporations based on fuzzy approach in order to offer MDBs an instrument to be able to choose low risk credit proposals.

As reported by Thun (2011) there are several standard sources of information required for assessing the borrowers default. In Figure 4.2 the essential information required for company credit scoring/rating is shown. These are industry risk and competitive in the market, management, ownership and corporate governance and financial soundness which includes profitability, liquidity and financial flexibility, and capitalisation. Moreover, the same information will be required for score the financial institutions except bank account data that can be substituted with relation with other financial institutions. However, as seen in the Figure 4.2 financial statement credit rating is the major component of the model therefore more important is given to that while designing the two separate scoring/rating models, one for corporation and one for financial institutions. Other than these factors, the impact of macroeconomic environment on the corporations and financial institutions financial soundness can also be take note of, shown in Figure 4.2.

There are three different methods to develop a scoring/rating method, one is solely based on data, the other one is solely based on expert judgments and third group is combination of the two which are referred to as hybrid models, both experts' judgments and data mining techniques are employed.

There are many criticisms over purely expert models as they only use the expert opinion, sometimes considered as bias if the expert group is changed. Therefore based on available past history of such customers, one can use hybrid models. Here it is the goal to reduce

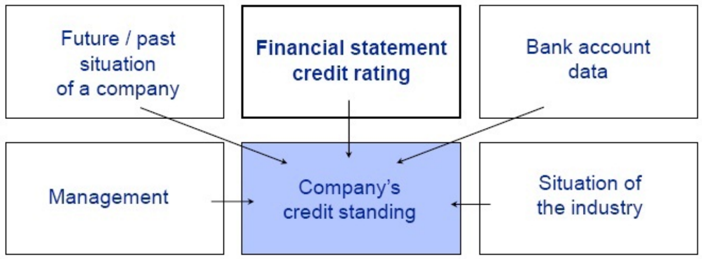


Figure 4.2: Sources of information to assess borrowers default risk Thun (2011)

or even eliminate the expert opinion as much as possible and try to quantify the fuzzy based scoring/rating models. One of the innovations in this paper in respect to the developed models is the employment of data mining techniques [4] In this chapter, a combination of data mining and fuzzy logic concept is used to calculate the credit risk of customers.

Nowadays numerous phenomenon in finance and economics are fuzzy but are treated as if they are crisp (Korol, 2012). The conception that a company or an individual is at risk of bankruptcy must be considered imprecise. In reality, the firms or individuals can be considered as 100% bankrupted in rare cases. It is difficult to determine the degree of bankruptcy threats using traditional statistical methods such as multivariate discriminant analysis. When the value of the discriminant function is less than the threshold value, it implies that the company is at risk of bankruptcies. However, with the use of fuzzy logic, vague and ambiguous concepts can be defined such as high risk or low risk.

Therefore, in the two models fuzzy logic concepts are applied to design a methodology for evaluating creditworthiness of the client.

[4]Data mining is the process of discovery of meaningful new correlation patterns and trends by sifting through large amount of data, using pattern recognition technologies as well as statistical and mathematical techniques. Data mining techniques can be considered descriptive or predictive. Descriptive data mining intends to summarize data and to highlight their interesting properties while predictive data mining techniques aims to build models to forecast future behaviours (Abdulsalam et al., 2012).

The value drivers, their respected membership functions and their influence on the credit scoring-rating need to be defined firstly in order to build a fuzzy logic model. Value drivers are defined using literature through regression models (see chapter 2 and 3).

Defining the shape of membership functions for each value drivers conducted employing statistical data and for retaining their influence on the credit scoring-rating regression model is used (see chapter 2 and 3).

This approach is alternative to the approach using neural networks approach where sufficient amount of data exists for customers who have defaulted.

In the case of MDBs - where there is low default loan portfolio- and in order to form a portfolio of credit customers -in this research mainly large corporations and FIs- with a reasonable quality, providing different type of credit facility to them such as participation in their equity or providing their working capital requirements, risk based price setting and keeping appropriate loan loss provisions, there is always need for classifying borrowers.

Models are formed based on the fundamental analysis[5] where both the internal and external factors are employed. The most important factor in fundamental analysis is information relating to the economy, the industry and the borrower itself. Therefore, fundamental analysis is broken into three distinct parts; a) borrower analysis, b) economy analysis and c) industry analysis where the company operates in (Tavakkoli et al., 2010) (see Figure 4.3).

Based on the regression analysis conducted in chapter 2 and 3 two scoring/rating models are proposed as shown in Figure 4.4 and Figure 4.5. These two credit models have some similarities and some differences. Both of them have intermediate variable levels which link the input variables and output variables and both has macroeconomic factors (e.g. inflation and GDP growth) and customer specific factors. Employing different value drivers are distinctive in the two models.

[5]In whole stock markets, generally, analysts employ several types of analysis; technical analysis, fundamental analysis and combination of these two methods. Technical analysis is the study of market behaviour, primarily through employing charts, for forecasting future price trends. A technical analyst holds the view that everything is concealed in price (Tavakkoli et al., 2010).

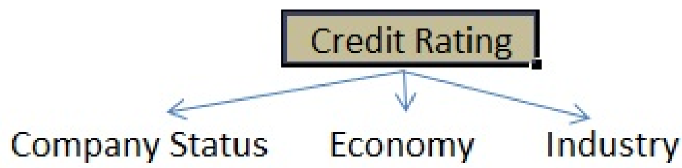


Figure 4.3: Credit scoring structure

Moreover, the concept of the two models in terms of scale of results - e.i in FI model our result scale is between 0 to 100 score (100 indicates risk free FI and 0 indicates an FI with the highest risk) and in corporation model the scale is from 0 to 1 (0 indicates for risk free corporation and 1 indicates a corporation with highest credit risk- are different. The third difference is that in the corporation model there is an extra intermediate category of privatisation, which takes care of privatisation environment in CIS countries, known for countries in transition. Seen in these two Figures, the input variables are grouped in two or three intermediate variables and this is for decreasing the numbers of fuzzy rules to be generated. Impact of each input variable on the intermediate variables and impacts of intermediate variables on output variable (scoring/rating) are marked with a question mark. These question marks will replace with percentages obtained from mapping the regression coefficients with percentages. It is worth noting that the summation of each group of variables linked to an intermediate variable must equal to one. This is why the regression coefficient result cannot be used directly in these models and a mapping process is needed.

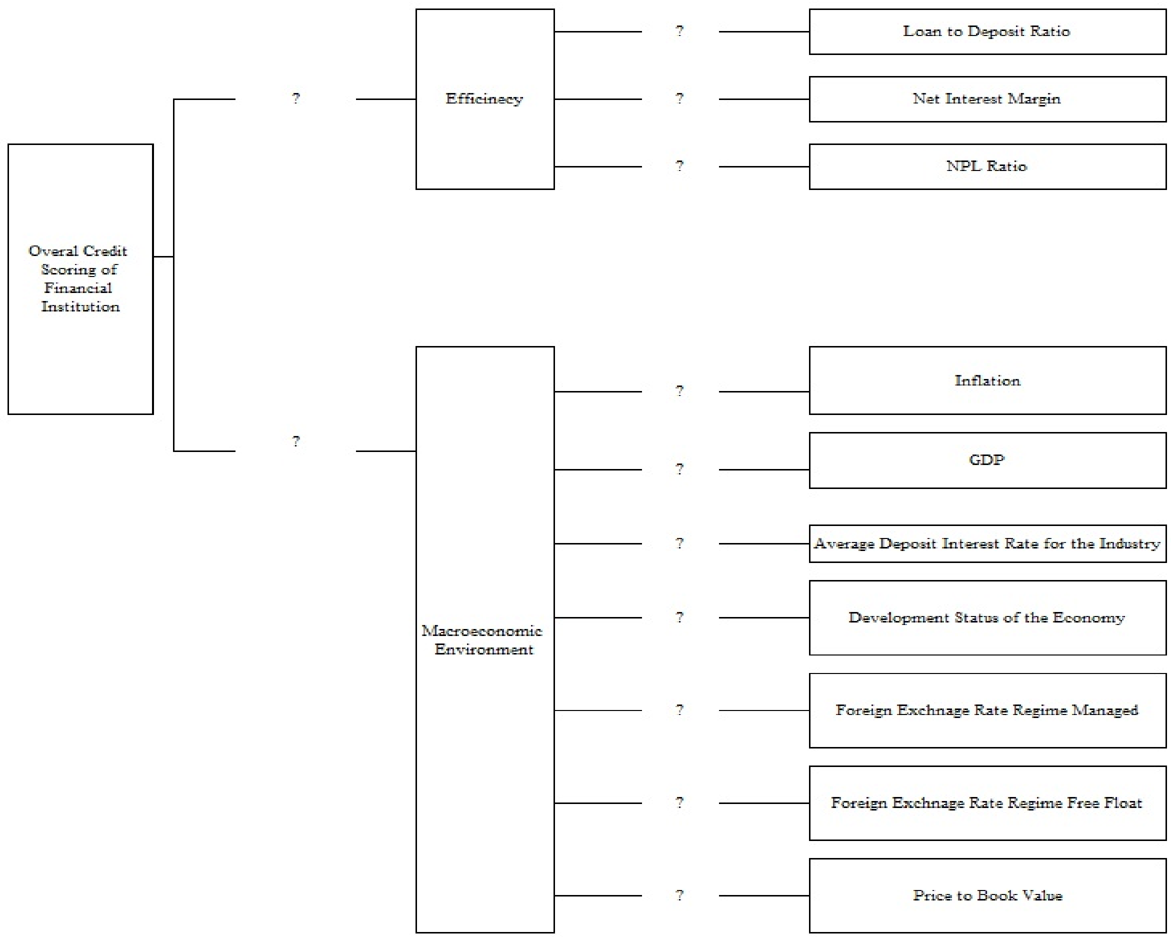


Figure 4.4: Proposed credit scoring structure for financial institutions

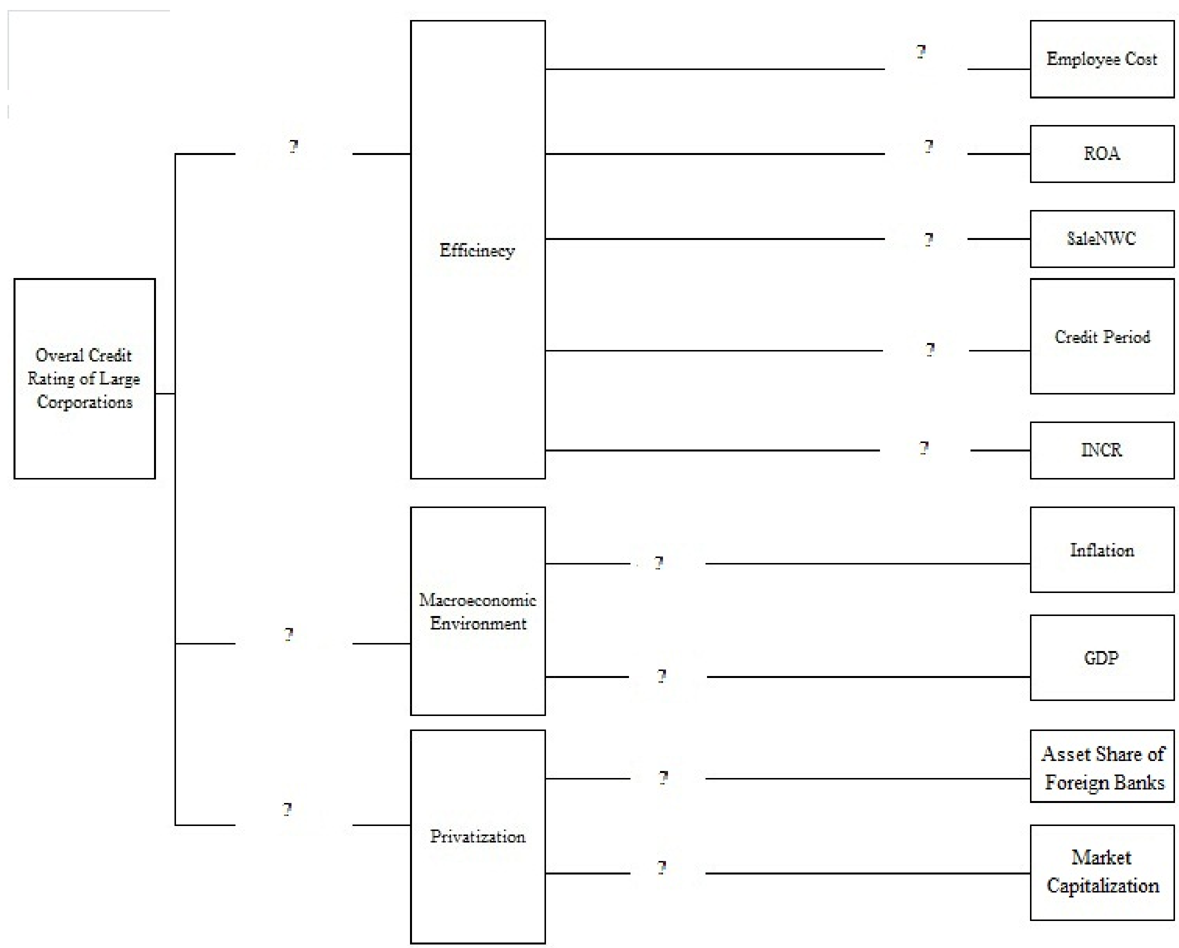


Figure 4.5: Proposed credit rating structure for very large corporations

If it is assumed that all the company's financial policies, their activities, their corporate governance, policies and strategies, their risk appetites, their expanding targets are for profit maximization, it is not exaggeration. It is true all these aspects are for one reason - making more profitability. Earning profit is essential for survival and growth of the company. Moreover, the need to profit is to create surplus for undertaking expansion and further investments. Profit enables one to meet the various expenditures during the stage of recession, profit is essential to attract capital for undertaking expansions, profit is needed for provision of risk bearing and finally profit is regarded as good measurement of efficiency because the performance of a business is judged based on its profit.

Therefore, profit as index is employed for firm financial soundness. Moreover, in previous chapters the main determinants of profitability by means of regression analysis for both the corporations and financial institutions are already determined and therefore those results form the basis for our two scoring/rating models. The determinants of profitability are assumed to be value drivers of scoring/rating results of the credit customers (output). However, for simplicity, through intermediate variables, the input variables are grouped.

The difference between the previous chapters and this chapter is that previously the study attempted to derive the main determinants of profitability for both the FIs and corporations and their coefficients. However, in this chapter, one attempts to go further and transform the research in a practical manner. Therefore as the fuzzy logic model is acceptable model for the low default portfolio case, used are the determined main value drivers and their quantified influences in our fuzzy scoring/rating models. In other words, instead of using expert judgment to define the value drivers' influences on the credit scoring/rating, the significance of each value drivers determined in previous chapters was used. Other advantages of the fuzzy based scoring/rating models are that unlike the regression models where it does not consider the median of the value drivers (descriptive variables) distribution, in our fuzzy logic model, the distribution shape is imposed to the value drivers. This is obtained by using the historical available data for each value driver and imposes it to its membership function. Therefore, a specific value for each value driver has different meaning. For instance, where the distribution is skewed to the left, having a low value of that value driver results in very low degree of membership for that. However, in the regression analysis such opportunity is not presented [6].

Therefore, financial and economic aspects are considered by focusing on several value drivers that are combined together via "if-then" rules. The output of the system is a real number in the interval [0, 1] for rating model results for corporations or a real number of [0,100] for scoring result of our financial institutions, which represents the credit risk of the customer. To corroborate the model, robustness checks are conducted. This scoring/rating system can be used for ranking firms, pricing and provisioning purposes.

Fuzzy logic is in this sense is an extremely effective tool since the complexity of real-life situations is handled through "vague" variables and "vague" interactions, which better replicate human mind in describing the phenomena. The mental processes of human beings are actually imperfect and imprecise, since individuals often act in contexts of incomplete (and unclear) information. The approach is just to show an application of fuzzy logic for appraising firms and financial institutions using the quantitative factors e.g. like the factors that have already determined in previous chapters. Another objective can be how a typical firm performed via-a-vis other similar firms.

Providing the ability to determine the place of each customer in comparison with other customers in respect to a specific value is considered as the other advantages of the fuzzy base scoring/rating method. In this regard, the major contribution of this piece of study is to include macro-economic factors in the internal scoring/rating Model. This is unlike the other past studies such as R.T.McIvor et al. (2004) where they just include the financial ratios to short list the companies for acquisition and employing the fuzzy logic concept solely in order to increase the accuracy of their model. The use of different scoring/rating models will be discussed in the literature review section.

[6] For instance in simple linear regression where α=$\bar{Y}$-β $\bar{X}$ and β=$\frac{COV(XY)}{VAR(X)}$ there is no trace of Median. Median is used in Skewness calculation ($\frac{\mu-\nu}{\sigma}$) where fuzzy value drivers MFs are impacted

Finally, the current chapter is organised as follows: the second section describes the fuzzy concept, fuzzy systems and fuzzy networks in detail. The third section presents a literature review of different credit scoring/rating models, focusing on the fuzzy concept application in finance. The forth chapter explains the data employed, in the fifth chapter, two customized fuzzy scoring/rating models are proposed followed by the last chapter, which explains the results as well as the conclusion remarks.

4.2 Fuzzy technique

As stated by Magni et al. (2006) "fuzzy logic is a cognitive framework that adequately replicates the natural way human beings recognize the world and think about problems and situations and enables us to formalize qualitative and vague concepts". This research predicts the integration of expert systems, statistical methods and fuzzy logic for company evaluation and, in general, for decision-making purposes represents a reliable methodology that could be appealing for managers, practitioners and analysts.

It does not excessively simplify description of reality, engage in complicated formalisation and neither requires advanced knowledge of mathematics. It is intuitive and comprehensible by any evaluator, extremely flexible (the evaluator can change it), able to handle both quantitative and qualitative variables and is not restricted to a small number of variables. At the same time, it does not renounce to formalisation and neither provides a suitable numerical value for the firm at hand. As the reader will note, the evaluation derives from logical implications ("if-then" rules). Implications include natural cognitive tools so anyone is able to understand and construct them.

4.2.1 Fuzzy logic concept (Fuzzy Set)

In the way in which the world is vague and multi-valued, fuzziness is often encountered in real life. As stated by Magni et al. (2006) in a business context, the sentence "the quality of the firm's products is high" is always true at a certain degree (possibly a zero degree) as well as the sentence "the quality of the firm's products is low" is always true at a certain degree (possibly zero). The term "fuzzy logic" emerged from the development of the theory of fuzzy sets by Lotfi Zadeh (1965), professor for computer science at the University of California, in Berkeley. Essentially, Fuzzy Logic (FL) is a multivariate logic that allows intermediate values to be defined between conventional evaluations such as true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers. As stated by Khcherem and Bouri (2009) a fuzzy set does not have specific and limited boundaries; the distinction between belonging or not, does not exist, but a degree of pertinence. Therefore, fuzzy logic rests on the assumption that all things belong to a set at a certain degree, so the quality of a product always belong to both the set of high-quality products and the set of low-quality products (to a certain degree), in the same sense a man always belongs to the set of old men at a certain degree (as well as to the set of young men at a certain degree). Moreover, qualitative variables such as competition in the industry, consistency with corporate strategy etc. may not be treated with the classic 'crisp' financial criteria and often are integrated in the decision process in a nonfinancial way or even neglected. In all these cases fuzzy logic may be used. Fuzzy logic enables the user to formalize linguistic attributes such as 'low', 'high', 'good', 'excellent', 'positive', 'interesting', 'fruitful', 'adequate' and so on. For a single variable, more attributes may be used and graphically represented in the same graph. As an example, the value drivers ROA is described by using three linguistic attributes; low, medium, high and the corresponding degrees. Graphically, one may represent these attributes through fuzzy numbers as in Figure 4.6. The x-axis collects all possible numerical values for ROA, whose unit of measure is given by profit after tax over total assets. The y-axis collects the degrees at which a linguistic attribute is activated (membership degrees). For this, Gaussian type of membership function is used[7]. For example, a ROA ratio of 2% is Low at a degree of 40%, Medium at degree of 30%, High at a zero degree. A ROA

[7]The famous Membership function types are given in Annexure C.1

of 40% is Low at a zero degree, Medium Low at a 30% degree, High at a degree of 50%. In other words, once the decision maker fixes a value for ROA ratio, the latter is fuzzified or translated into fuzzy terms and the corresponding fuzzy numbers is individuated by the pair. Membership functions are usually presented in graphical forms like ones shown in Figure 4.6.

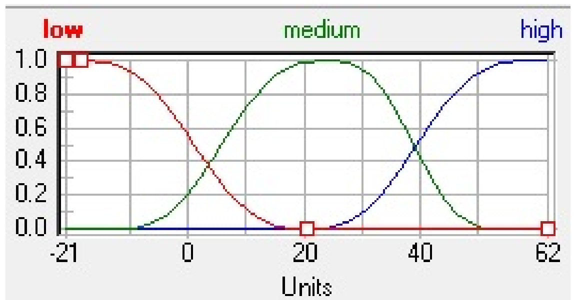


Figure 4.6: Example of Fuzzy Membership Function for ROA

4.2.2 Fuzzy system

Fuzzy logic involves a system of concepts, principals and methods of dealing with modes of reasoning that are approximate, rather than being exact or precise. It is particularly effective at handling uncertainty, vagueness and imprecision and it is especially useful where a problem can be described linguistically (using words). In fuzzy logic the degree of truth of a statement can range between the value of 0 and 1 and is not constrained to two truth values true, false as found in classic predicate logic (Khcherem and Bouri, 2009).

The point where FL emerges becomes the crisis in relation to classic set theory. One member definitely belongs or does not belong to the set in classic set theory. In other words, there are two possibilities, an individual is a member of a set or either not a member of a set. Hence, FL makes it possible that one individual can be a member of more than one set in a certain degree by means of membership functions. A is defined as a fuzzy set as shown below (Korol, 2012).

$$A = \{(x, \mu_A(x))|x \in \chi\} \tag{4.2}$$

This equation $\mu_A(x)$:$\chi \rightarrow [0,1]$ is a function for each element of χ that determines the extent to which it belongs to set A. This function is referred to as a membership function of fuzzy set A which gets value between 0 and 1. Thus, the membership function $\mu_A(x) : U \Longrightarrow [0,1]$ is defined as follow:

$$\forall_{x \in U} \mu_A(x) = \begin{cases} f(x), & x \in \chi \\ 0 & x \notin \chi \end{cases}$$

Where $\mu_A(x)$ function defines membership of element x to set A, which is subset of $U; f(x)-$ function receiving values from interval [0,1]. The value of this function is referred to as the degrees of membership. A membership function assigns the degree of membership of each element $x \in \chi$ to a fuzzy set A, where three situations can be distinguished:

- $\mu_A(x) = 1$ means full membership of element x to the fuzzy set A,
- $\mu_A(x) = 0$ means that no element x belongs to fuzzy set A,
- $0 < \mu_A(x) < 1$ means partial membership of an element x to the fuzzy set A.

Fuzzy expert systems use fuzzy data, fuzzy rules, and fuzzy inference. For example, in case of the corporate model used, a simple rule based on conditional ("if-then") implications is described as follows:

IF last year ROA is medium at a degree of x AND the inflation is high at a degree of y AND the market capitalization is low at a degree of z THEN the credit risk is high at a degree of w

With x, y, z, w being real number in [0,1]. If the system receives the piece of information provided by the above antecedent, it infers (using its inferential engine) the sentence "the credit risk is high" and simultaneously provides a corresponding degree w that substantiates such a "high" value. The value of w is obtained through aggregation of the membership degrees x, y, z of the antecedent variables (Magni et al., 2006). One feature of FSs is the ability to realise a complex nonlinear input output relation as a synthesis of multiple simple input-output relations. This idea is similar to that of NNs. The simple input-output relation is described in each rule. The boundary of the rule areas is not sharp, but *fuzzy*. This is the fundamental idea of FSs and the origin of the term 'fuzzy' (Takagi, 1997)

Therefore, fuzzy systems have two blocks: first involves designing the antecedent part and the second involves designing the consequent part.

Design of antecedent parts Designing antecedent parts refers to deciding how to partition an input space. Most rule-based systems assume that all input variables are independent and partition the input space of each variable. The difference between crisp and fuzzy rule-based systems is how the input space is partitioned (compare Figure 4.7; (a) with (b).) The idea of FSs is based on the premise that in the real analogue world, change is not catastrophic but gradual in nature. Fuzzy systems, then, allow overlapping rule areas to shift from one control rule to another. The degree of this overlapping is defined by membership functions. The gradual characteristics allow smooth fuzzy control (Takagi, 1997). It should be noted that the use of fuzzy numbers for even[8] the numeric intervals is more representative than the original numerical intervals. The issue appears to be the sharp transition from one interval to another interval. This is why fuzzy logic rules are used to obtain the scoring/rating. Otherwise, the future ROA could be calculated based on predicted numbers by inserting them in estimated regression formula. However, fuzzy will be used with its ability of smooth control instead of sharp transmission through using the predicted numbers of value drivers and fuzzy rules.

Design of consequent parts or Fuzzy Inference System Fuzzy inference is the process of formulating and mapping from a given input to an output using fuzzy logic. The process of fuzzy inference involves all pieces of membership functions, fuzzy logic operators and if-then rules. The fuzzy inference system forms a useful computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and

[8]For non-numerical intervals using the fuzzy numbers is a must.

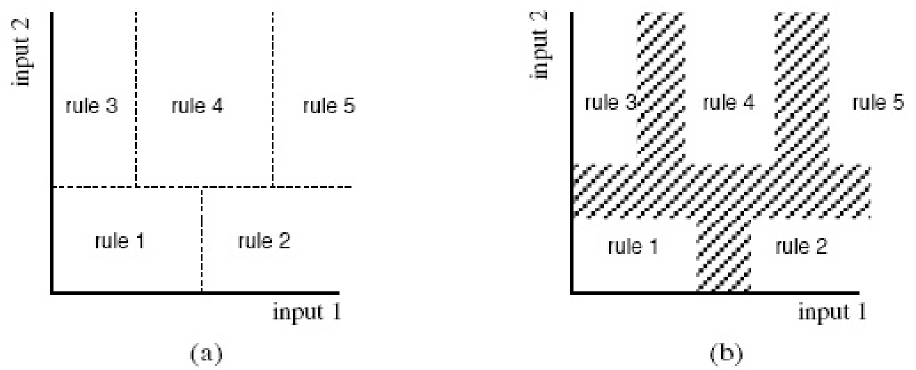


Figure 4.7: Rule partition of an input space: (a) partition for crisp rules and (b) partition for fuzzy rules.
Takagi (1997)

fuzzy reasoning. This system has been successfully applied in various fields such as automatic control, expert systems and computer vision. The fuzzy inference system is a powerful function approximate, and it differs from other powerful function approximate, neural networks, in its capability of handling linguistic information. The basic structure of a fuzzy inference system consists of three conceptual components:

(1) a rule base, which contains a selection of fuzzy rules; (2) a database, which defines the membership functions used in the fuzzy rules; and (3) a reasoning mechanism, which performs the inference procedure upon the rules to derive a reasonable output. The fuzzy rules are usually called fuzzy if-then rules and are described in the following forms:

$$R : if\ x_1\ is\ F_1\ ,\ and\ x_2\ is\ F_2\ ...\ and\ X_p\ is\ F_p\ ,\ then\ Y\ is\ G, \quad (4.3)$$

Where F_i, $i = 1, ..., p$, and G are linguistic terms which are fuzzy sets defined by membership functions, and $X = (X_l, ..., X_p)^T$ and Y are the input and output linguistic variables, respectively. The statement in the antecedent or premise represents the input information and the statement in the consequence or conclusion represents the output. Furthermore, in order to derive conclusions from a set of fuzzy if-then rules, an inference procedure is needed, which is called fuzzy reasoning or approximate reasoning. These reasoning procedures derive conclusions based on information aggregated from all the rules. Different types of fuzzy if-then rules and aggregation methods lead to different fuzzy inference systems. There are two primary types of fuzzy inference systems developed for function approximation: *Mamdani-type* and *Sugeno-type* (see Appendix C.1 and Appendix C.2 (Sivanandam et al., 2007) and Corporation (2002)). These two types of inference systems vary in the manner in which the outputs are determined.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology in use. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani as an attempt to control a steam engine and boiler combination by synthesising a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes. Mamdani-type inference, expects the output membership functions to be fuzzy sets. Following the aggregation process, each output fuzzy set requires de-fuzzification. It is possible, and in many cases more efficient to use a single spike as the output membership function rather than a distributed fuzzy set. This is occasionally referred to as a singleton output membership function. Sugeno-type systems support this type of model. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant (Corporation, 2002). Formulation of Mamdani and Takagi-Sugano is defined below as:

1. Mamdani model: $y = A$ (A is a fuzzy number.)
2. TSK model: $y = a_0 + \sum a_i x_i$ (a_i is a constant, and x_i is an input variable.)

The fuzzy inference system proposed by Takagi and Sugeno, which is known as the Sugeno fuzzy model or Sugeno fuzzy inference system would be used in this investigation. Instead of the if-then rules listed in equation (4.3), Takagi and Sugeno proposed the following fuzzy rule:

$$R^l : if(x_1\ is\ F_1^l\, and\ x_2\ is\ F_2^l\ ...\ and\ X_p\ is\ F_p^l) \tag{4.4}$$

then

$$(Y = Y^1 = C_0^l + C_1^l x_1 + ... + C_p^l x_p) \tag{4.5}$$

In which F_i^l represents fuzzy set or fuzzy terms associated with the input x_i in the lth rule, Y^l is the system output due to rule R^l, and there are m rules, $l = 1, 2, ..., m$. In Sugeno fuzzy system, c_i^l represents real-valued parameter. In the present application, c_i^l will be assumed to be a fuzzy number including the variables priority as well. Thus, the consequence in (4.5) is a possibilistic linear equation. For a real-valued input vector $X = (x^l, ..., Xp)^T$, the overall output of the Sugeno fuzzy system is a weighted average of the Y^l

$$y^l = \frac{\sum_{l=1}^m w^l y^l}{\sum_{l=1}^m w^l} \tag{4.6}$$

Where the weight w^l implies the truth value of the proposition rules $Y = Y^l$ or rules weights and is defined as:

$$w^l = \Pi_{i=1}^p \mu_{F_i^l}(x_i) \tag{4.7}$$

Where $\mu_{F_i^l}(x_i)$ is a membership function defined on the fuzzy set F_i^l. In the equation above, w^l is defined in terms of a "product" operator on the membership functions, w^l can also be defined differently such as the "min" operator.

4.2.3 Fuzzy computation layers

Explained here is the Sugeno Fuzzy system in detail. Essentially, fuzzy system can be defined in five-layer calculation and it is illustrated in Figure 4.8. The network is composed of nodes inter-connected through directional links. Nodes contain parameters and are represented by circles or squares. Square nodes represent nodes with parameters and circle nodes represent fixed nodes without parameters. To illustrate how a fuzzy inference system can be represented by Fuzzy Network (FN), one can consider the following example (Cheng and Lee, 1999). If assumed that a fuzzy inference system contains the following four rules:

$$R_1 : if(x_1\ is\ small\ and\ x_2\ is\ low) \tag{4.8}$$

then

$$(Y = Y^1 = C_l + C_{11}x_1 + ... + C_{12}x_2) \tag{4.9}$$

$$R_2 : if\ (x_1\ is\ Small\ and\ x_2\ is\ High) \tag{4.10}$$

then

$$(Y = Y_2 = C_2 + C_{21}x_1 + C_{22}x_2) \tag{4.11}$$

$$R_3 : if\ (x_1\ is\ Large\ and\ x_2\ is\ Low) \tag{4.12}$$

then

$$(Y = Y_3 = C_3 + C_{31}x_1 + C_{32}x_2) \tag{4.13}$$

$$R_4 : if\ (x_1\ is\ Large\ and\ x_2\ is\ High) \tag{4.14}$$

then

$$(Y = Y_4 = C_4 + C_{41}x_1 + C_{42}x_2) \tag{4.15}$$

This system possesses a two-dimensional input, $X = (x_1, x_2)^T$. For input x_1, there are two fuzzy sets, “small” and “large” associated and for input x_2, two fuzzy sets of “low” and “high” are associated.

Two subgroups of nodes in Layer 1 exist. The first subgroup includes nodes “small” and “large”, which are linked by x_1; and the second subgroup includes nodes “low” and “high”, which are linked

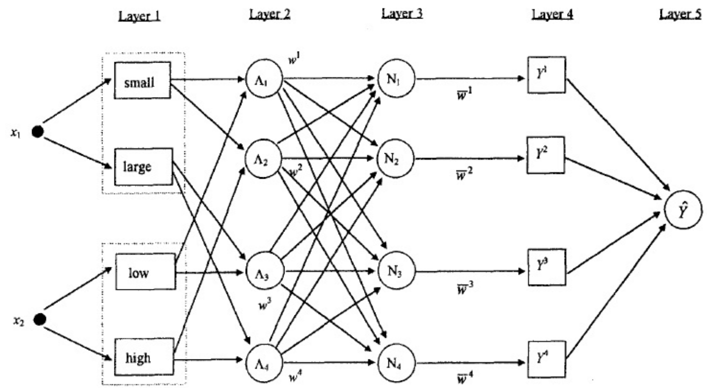


Figure 4.8: Architecture of FAN for the illustrative example. Cheng and Lee (1999)

by x_2. Each node in Layer 1 outputs a membership function based on the linguistic value of the input. Nodes in Layer 2 output the products which are w^l, $l = 1, ..., 4$, based on the incoming signals. The function of a node in this layer is to synthesize the information in the premise section of the fuzzy if-then rule. For example, node 1 in Layer 2, $\Lambda 1$, receives signals from "small" and "low", which is equivalent to the premise of $R1$ in the above fuzzy inference system. The number of nodes in Layer 2 is the number of combinations of nodes from each subgroup in Layer 1, for instance two variables exist, each has 2 MF so there will be $2^2 = 4$ rules. Layer 3 simply performs a normalization of the output signals from Layer 2. Each node in Layer 4 corresponds to the consequence of each fuzzy if-then rule. For example, the first node $y1$ in Layer 4 is defined as $y^l = c_0^1 + c_1^1 x_1 + c_2^1 x_2$. Finally, Layer 5 sums up all the outputs from Layer 4, which is equivalent to performing an aggregation of all the four fuzzy if-then rules.

The output of node h in layer r is denoted as $f_{r,h}$, then the functions of each node in Figures 4.8 can be described as follows:

LAYER 1 . Let the fuzzy sets, "small", "large", "low", and "high", in the premise section of fuzzy if-then rules be denote by F_1, F_2, F_3, and F_4, respectively. The output of node h is defined by the membership function on F_h, $f_{l,h} = \mu F_h(X_1)$, for $h = 1, 2$ and $f_{l,h} =$

$\mu F_h(X_2)$, for $h = 3, 4$. The membership function for F_h can be any appropriated function. In this investigation, a Gaussian function is assumed whose parameters can be represented by the parameter set υ_h, σ_h,

$$F_h(X_1) = exp[-(\frac{x_1 - \upsilon_h}{\sigma_h})^2],\ for\ h = 1, 2 \tag{4.16}$$

and

$$F_h(X_2) = exp[-(\frac{x_2 - \upsilon_h}{\sigma_h})^2],\ for\ h = 3, 4 \tag{4.17}$$

The parameter set υ_h, σ_h in this layer is referred to as the premise parameters.

LAYER 2 Every node in this layer is a fixed node labeled Λ_l, $l = 1, ..., 4$. The nodes in this layer act as fuzzy and operate in the premise section of the fuzzy if-then rule. Each node has exactly two incoming signals from Layer 1. Here, weights are defined as a multiplication of the incoming signals. This multiplied output forms the firing strength w^l for rule l:

$$f2, 1 : W^1 = \mu F_1(X_1).\mu F_3(X_2) \tag{4.18}$$
$$f2, 2 : W^2 = \mu F_1(X_1).\mu F_4(X_2) \tag{4.19}$$
$$f2, 3 : W^3 = \mu F_2(X_1).\mu F_3(X_2) \tag{4.20}$$
$$f2, 4 : W^4 = \mu F_2(X_1).\mu F_4(X_2) \tag{4.21}$$

LAYER 3. Nodes in this layer are fixed nodes labeled $N_l, l = 1, ..., 4$. The output of this layer is a normalisation of the outputs of Layer 2:

$$f_{3,l} = w\tilde{-}^l = \frac{w^l}{\sum_{t=1}^{m} w^t}, l = 1...., 4 \tag{4.22}$$

LAYER 4. The nodes in this layer are adaptive nodes with nodes function

$$f_{4,l} = \bar{w}^l Y_l, l = 1....,4 \tag{4.23}$$

where Y^l is the consequent part of a fuzzy if-then rule, and

$$Y^l = c_0^l + c_1^l x_1 + c_2^l x_2 \tag{4.24}$$

Where c_i^l are fuzzy numbers and are referred to as the consequence parameters. It is assumed that C_j^l are symmetrical triangular fuzzy numbers as $c_j^l = (a_j^l, b_j^l)$, $j = 0, ...p$, $l = 1, ..., m$. (Jiao et al., 2007), which also includes the variable influence. This is shown in an example in Annexure **??**. Here, is the place where variable influences are incorporated.

LAYER 5. . The single node in this layer is a fixed node, which computes the overall output as the summation of all the incoming signals:

$$f_{5,1} = \hat{Y} = \sum_{l=1}^{4} Y^l \tag{4.25}$$

A numerical example of this case is shown in Appendix **??**.

4.2.4 Fuzzy network structure

After the fuzzy network calculation layers are defined, the case will be further explored in terms of input variables, their direct or indirect effects on outputs and its network structure. For instance, let us assume (b1) structure in Figure 4.9 where there are two nodes +2 and +3 and four leaves of x1, x2, x3, x4. In addition, the output of each non-leaf node is calculated as a single TS fuzzy sub-model. Figure 4.9 illustrates the tree structural representation of the hierarchical TS fuzzy models. This is similar to the decision tree scoring models also referred to as Bayesian Network or Recursive partitioning algorithm[9]. It should be noted that, in order to calculate the output of each TS fuzzy sub-model (non-leaf node), parameters in the antecedent parts and consequent parts of the TS fuzzy sub-model should be embedded into the tree (Yuehui and Ajith, 2010).

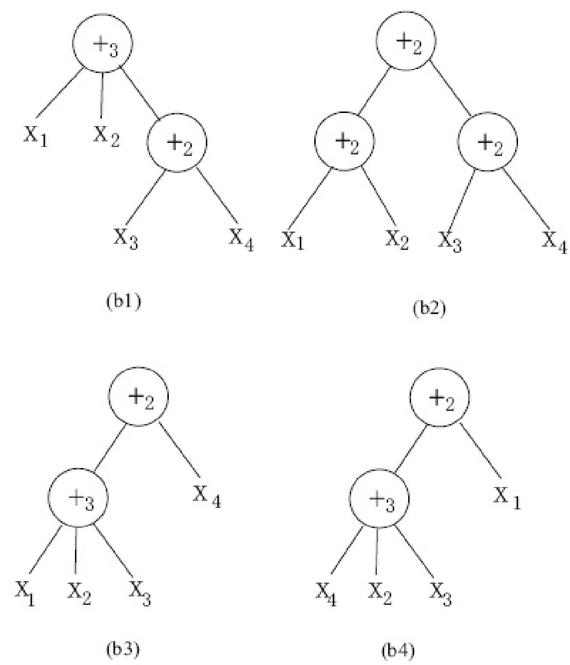


Figure 4.9: Tree structural representation of the hierarchical T-S fuzzy models

Yuehui and Ajith (2010)

The output of a hierarchical TS-FS tree can be calculated on a layer to layer basis. For simplicity, the calculation process of the tree is illustrated below. It is assumed that each input variable is divided into two fuzzy sets and the given fuzzy membership function is:

$$\mu(a, b; x) = \frac{1}{1 + (\frac{x-a}{b})^2} \tag{4.26}$$

[9]See Abramowicz et al. (2003) for application of such methods.

First, the output of TS fuzzy sub-model (node +2) is computed. It is assumed that the given fuzzy sets for variables x3 and x4 are A_{11}, A_{12} and A_{21}, A_{22}, respectively. Also, suppose that the parameters in the consequent parts of rule base are $c^0_{ij}, c^1_{ij}, c^2_{ij}$, $(i = 1, 2\ and\ j = 1, 2)$. These parameters are encoded in the node $+_2$. Therefore, the corresponding fuzzy rules of node $+_2$ can be described as:

$$R_{j,j} : if\ (x_3\ is\ A_{1,i}\ and\ x_4\ is\ A_{2j}) \tag{4.27}$$
$$then\ (y_{ij} = c^0_{ij} + c^1_{ij}x_3 + c^2_{ij}x_4) \tag{4.28}$$
$$for\ i = 1, 2\ and\ j = 1, 2. \tag{4.29}$$

The output of node $+_2$ can be calculated based on the TS fuzzy model:

$$\mu(a, b; x) = \frac{\sum_{i=1}^{2}\sum_{j=1}^{2}\sigma_{ij}y_{ij}}{\sum_{i=1}^{2}\sum_{j=1}^{2}\sigma_{ij}} \tag{4.30}$$

Where $\sigma_{ij} = \mu_{A1i}(x_3)\mu_{A2j}(x_4)$ for $i = 1, 2$ and $j = 1, 2$.

Second, the overall output of the hierarchical TS fuzzy model is computed. It has three input x_1, x_2 and y (the output of the TS fuzzy sub-model (node $+_2$)). Assume that the used fuzzy sets for variables x_1, x_2 and y are: $B_{11}, B_{12}, B_{21}, B_{22}, B_{31}$ and B_{32}, respectively. Suppose that the parameters in the consequent parts of rule base are d^0_{ijl}, d^1_{ijl}, d^2_{ijl} and d^3_{ijl}, $(i = 1, 2, j = 1, 2$ and $l = 1, 2)$. Theses parameters are encoded in node $+_3$. the complete fuzzy rules of node $+_3$ can be describe as follows:

$$R_{j,j} : if\ (x_1\ is\ B_{1,i}\ x_2\ is\ B_{2j}\ and\ y\ is B_{3l}) \tag{4.31}$$
$$then\ (z_{ijl} = d^0_{ijl} + d^1_{ijl}x_1 + d^2_{ijl}x_2 + d^3_{ijl}y) \tag{4.32}$$
$$for\ i = 1, 2\ j = 1, 2\ and\ l = 1, 2. \tag{4.33}$$

Thus, the overall output of the tree is:

$$z = \frac{\sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{l=1}^{2}\mu_{ijl}z_{ijl}}{\sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{l=1}^{2}\mu_{i,j,l}} \tag{4.34}$$

Where $\mu_{ijl}(x_1, x_2, y) = \mu_{B1i}(x_1)\mu_{B2j}(x_2)\mu_{B3l}(y)$

Now, assume again that the structure (b1) and instead of 2 Membership function for inputs (leavses), there is 5 MF and 7 MF for inputs and intermediate variables (nodes). In this case, the first layer will have $25 = 5^2$[10] rules and for the second layer would totally have $175 = 7(5)^2$ rules. If imagined that 4 variables are directly linked to the output node (no hierarchical structure or no existence of node +2), then $625 = (5)^4$ rules would be generated(Zajaczkowski and Verma, 2012). Therefore, the more the hierarchy is used the less rules and the less complicated the fuzzy models are likely to be.

4.2.5 Fuzzy Logic Numerical Example

A simple fuzzy network structure is shown through a numerical example shown in Table 4.1 in the following. For simplicity several assumption have been made; a)two value drivers are selected, each of which has positive influence on the fuzzy output. b)each value driver defined to have two membership functions. Value driver 1 has small and large and value driver 2 has low and high membership function. 1 represent low and small membership functions and 2 represent high and large membe4rship functions, c)each membership functions in each value driver has 50 percent overlapping see Figure 4.10, d)value driver 2 has two times more influence than value driver 1. Here several main concepts needs to be explained before starting the fuzzy layers.

Fuzzy Numbers Fuzzy numbers represent each membership functions. In this example 1 indicates low and small and 2 indicates high and large. Those are shown in Cells D6, D13, E6 and E13.

Fuzzy Membership Function Fuzzy membership function is a function which defines the degree of membership. In the example linear function is employed. It calculates as the actual value (any value

[10] Each domain region for input variables x is divided into 5 overlapping intervals covered by membership function sets A_j^k, k=1,...,5 encoded as integer 1 to 5. The intermediate variable and output/nodes are divided into 7 regions covered by membership sets B_j^k, k=1,...,7.

between 1 and 10 for value driver 1 and any value between 1 and 50 for value driver 2), shown in cells F6 and F13, divided by maximum value. For instance for value driver 1, value of 8 indicates 8 divided by 10 (maximum value) which produce 0.8 degree of membership to membership function large or 0.2 degree of membership to membership function small. In case of value driver 2, 45 divided by 50 (maximum value) which produce 0.9 degree of membership to membership function High and 0.1 degree of membership to membership function low (see Figure 4.10). These membership functions are shown in D8, E8, D15 and E15.

Value Driver's Value For each value drivers there are minimum and maximum values where the actual value fall in between. For instance for value driver 1, the minimum and maximum value are 0 and 10 and for value driver 2 the minimum and maximum value are 0 and 50. In the example 8 and 45 defined as value drivers value which falls between 10 and 50 respectively. These values are shown in cells F6 and F13 for the two value drivers.

Value Driver's influences Value driver 2 has double influence on fuzzy results compared to value driver 1. This is shown in cells G6 and G13 as 2 for value driver 2 versus 1 for value driver 1.

After explaining the main concepts, here the five computation layers are given. In layer 1, the multiplication of fuzzy numbers, fuzzy membership functions and value drivers influence for each fuzzy set is calculated. For instance, for membership small, the calculation is given in cell D19 by following the formula of D8*D6*I6 which produce 0.2. For other membership function of large, low and high the calculated numbers are 1.6, 0.2 and 3.6. The membership function High has the most calculated value of 3.6. This is as result of its high value of 45 compared to 8 in value driver 1 and its double influence compared to value driver 1.

In layer2, four rules are defined which are combinations of one membership function from each value drivers. Each rules calculated as multiplication of the results in Layer 1. For instance rule 1 which is defined as IF value driver 1 has small and value driver 2 has low membership function. This is being done by multiplying 0.2 and 0.2 which results in 0.04. The other three if then rules define similarly as IF Small and High, IF Large and Low and IF Large and High. The numerical results are given in row 22.

In layer 3, results from layer 2 are being normalized. This is being done through dividing each output (row 22) by the their summation. These are called normalized weight of each rule. The respected results are shown in row 24.

Before starting Layer 4, a pre-calculations is required and that is the multiplication of fuzzy number by actual value and the value driver's influence. In this example the results will be shown in row 28. Now Layer 4 can be started by multiplying the row 28 and the normalized rules' weights. This is shown in row 30.

Finally in layer 5, the results of layer 4 are being aggregated as shown in row 31 as a single value of 180. Worth mentioning that the maximum value that this cell can get is 220. By this simple numerical example, an attempt was made to show how computation are conducted in each layer and how the result is generated in the fifth or final layer. As it was shown numerically the process consisted of four IF-THEN rules which formed the body of the fuzzy network.

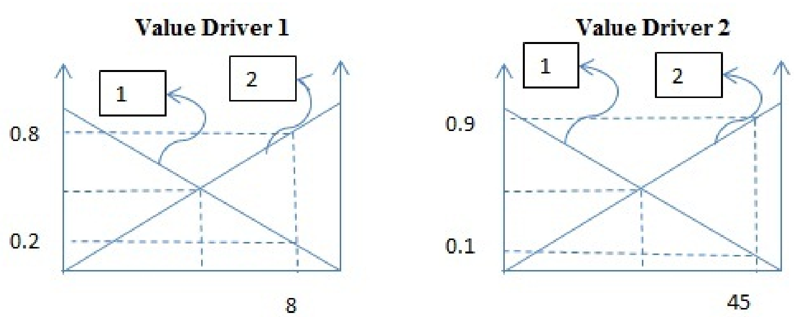


Figure 4.10: Value Drivers

	A	B	C	D	E	F	G	H
2				Membership Functions				
3								
4			Value Driver 1	Small	Large	Actual values (x) from 1-10	Variable influence from 0-2	
5				Fuzzy Numbers	Fuzzy Numbers			max
6				1	2	8	1	10
7				=1-E8	muF_h(x)			
8				0.2	0.8			
10				Low	High			
11								
12				Fuzzy Numbers				max
13			Value Driver 2	1	2	45	2	50
14				muF_h(x)				
15				0.1	0.9			
17				=D8*D6*$I$6	Value Driver 1	Value Driver 2		
18				Small	=E8*E6*$I$6	Low	High	
19		Layer1	muF(x)	0.2	1.6	0.2	3.6	
20				=D19*F19	=D19*G19	=E19*F19	=E19*G19	
21				Small & Low	Small and High	Large & Low	Large & High	
22		Layer2	w	0.04	0.72	0.32	5.76	
23			=D22/SUM($D$22:$G$22)					
24		Layer3	Normalized w	0.01	0.11	0.05	0.84	1
25								
26				Small& Low	Small&High	Large&Low	Large$High	
27		Yl		=(D6*$G$6*F6)+(D13*$G$13*F13)	=(D6*$G$6*F6)+(E6*$G$6*F13)	=(E6*$G$6*F6)+(F13*D13*$G$13)	=(E6*$G$6*F6)+(F13*E13*$G$13)	
28		Yl		98	98	106	196	
29		Layer4		=D28*D24	=E28*E24	=F28*F24	=G28*G24	
30		Layer4		0.573099415	10.31578947	4.959064327	165.0526316	
31		Layer5	Y =SUM(D30:G30)	180.9005848				

Table 4.1: Numerical example-fuzzy number calculations

4.3 Literature review

In literature, numerous researches exist which have undertaken credit risk measurement and more specifically, relate to credit scoring/rating models. There are wide range of scoring/rating models[11] ranges from parametric (Statistical)[12] to non-parametric (non-statistical and expert judgment models) scoring/rating models[13]. However, the intermediate solution is to blend some judgmental view with the statistical results. As parametric models different types of regression models can be referred to such as linear probability model, Logit and Probit models, discriminant analysis models[14] and for non-parametric approaches decision tree scoring models can be referred to[15] (also called classification trees or recursive partitioning algorithms), mathematical programming, nearest neighbors models, analytical hierarchy processes, soft computing techniques[16] such as neural networks (e.g Multi-Layered Feed-Forward Neural Network (MLFN) or Probabilistic neural network (PNN)[17], genetic algorithm techniques, fuzzy logic and combination of these two mentioned methods, called Neuro-Fuzzy methods. However, as previously mentioned, all the above-mentioned statistical methods are ruled out when faced with low or zero default credit portfolios where default history is almost nil. Therefore, one of the less statistical scoring models is chosen, which in this case has been the selection of a fuzzy model, which is validated using historical data.

Fuzzy systems applied in different fields, range from its application in engineering (see Khodaverdi et al. (2009)) for instance, in the prediction of aircraft performance after take-off (Hossain et al., 2011), its medical applications in monitoring glaucoma by means of a neuro-fuzzy classifier (Huang et al., 2007), its application in house good productions such as washing machines (Lucas et al., 2006), the applica-

[11]see Kiss (2003), Peng and Kou (2008) and Vojtek and Koeenda (2005)

[12]Past data of a number of customers are evaluated statistically to identify a set of predictors to predict the new customers credit worthiness.

[13]see Lee (2010) for Analytic Hierarchy Process and Networks (AHP and ANP)

[14]see study done by Bardos (2001)

[15]see Abramowicz et al. (2003)

[16]see Lahsahna et al. (2010)

[17]see Limsombunchai et al. (2005) for more details

tion in evaluation of concrete waste management options (Khodaverdi et al., 2009)) and in Geomatics Kordi (2008) to its application in business and finance (see Khcherem and Bouri (2009) where fuzzy concept is used to develop a buy/sell investment strategy model, Kwong and Bai (2002), Ravi et al. (2010), Moeinzadeh and Hajfathaliha (2010) and Shen et al. (2010)) which sharply increased in recent years. Numerous studies exist on the predictive power of fuzzy logic systems over other methods of credit scoring and fuzzy logic has practical applications in many cases. In literature the studies are categorised into two groups of studies, in one group fuzzy models designed employing expert judgments to create the fuzzy rules, in the other group neuro-fuzzy models are built based on default history data. In this piece of study the research's models stand in between these two categories as fuzzy logic concept is used in combination with data mining techniques (regression analysis). As an example of using fuzzy logic in the business decision-making the application of fuzzy system is referred to automate the risk assessment evaluation for car leasing contracts. In which BMW Bank and Inform Software GMBH of Germany have developed a fuzzy enhanced score card system (Edisbury et al., 1999). The primary goal of BMW Bank was to take the decision process away from the bank and give it to the car dealer, which allowed the dealer to assess the customers independently, rather than waiting for BMW bank to approve a leasing contract. In this plan, they have developed fuzzy decision-making systems for private customers and for corporate entities. As reported, their total fuzzy logic system involved 413 fuzzy rules in three modules. The entire design, test and verification of the three modules took two person-year efforts and integrating the modules generated by FuzzyTech into PC-Based software for leasing contract management required another person month. The system is currently in operation at German BMW dealers, and BMW Bank management considers the performance to be equivalent to an experienced leasing contract expert. Although BMW Bank has not published a detailed cost saving analysis, a quick estimation can be undertaken based on 50,000 leasing contracts per year and total evaluation time of 30 minutes for each leasing contract (including obtaining credit history information) results in 25,000 person hours or 14-person year. Therefore, compared to the cost of the fuzzy logic decision support system implementation and maintenance, the savings are substantial. For private customers they used a simple network model consist of scoring root, resulted from customer profile node and three independent value drivers of back-paying, credit history and monthly payment ratio. The customer profile consists of 6 value drivers and 2 nodes. In the customer profile, they consider unemployment value driver, which comes from a database that stores the unemployment rate for the customer profession. The other independent value drivers such as back-paying history of the customer is measure how timely they have been paying previous loan agreements. The other value driver monthly payment ratio is calculated as monthly payment over monthly disposable income of the customers. For corporate customers their root is scoring which resulted from two nodes and two independent value drivers. One node is illiquid risk, which is resulted on two other nodes of financial backing (resulting capital and revenue value drivers) and company structure (number of employees, company age and legal type value drivers). The other node is credit evaluation, which resulted to two value drivers of Indexcredi and Inforcredit which both come from information service providers that maintain credit scorings for every company in Germany.

In other research undertaken by (R.T.McIvor et al., 2004) it was shown how a fuzzy system can be effectively utilised to evaluate a large source of financial data while applying preferences to particular inputs within the analysis. Five stages have been used: 1) entering the companies profile, 2) preliminary identification, 3) financial analysis of potential companies, 4) analysis of selected companies and 5) establish acquisition programme including a fuzzy stage. For the fuzzy system a 2-layer structure has been used, which consists of financial categories and aggregation level. 4 categories of financial ratios (profitability, efficiency, liquidity, financial strength and gearing), and Takagi-Sugeno-Kang (TSK) method as the fuzzy inference method and Heuristic selection[18] as selecting method for parameters of membership functions have been used. Magni et al. (2006) in another study constructed their model base on three segment of *Equity*

[18]The other methods are Clustering approach, C-mean clustering approach, Adaptive vector quantification and self-organizing map

value, *Additional Financial Value* and *Synergies* purely based on expert judgments to create the if-then rules. Each segment had several factors e.g. additional financial value, one of the three fundamental building blocks of the model identifies the financial value that could be created through an optimization of the capital structure of the target firm. Therefore, in this study the three firm valuing segments; in turn depend on others variables until, proceeding backward, a set of initial independent variables (the inputs) is reached. Moreover, several value drivers had multi-effect on the different nodes and occasionally on the root at the same time. They expected the final output to measures the value-creation power of the firm and it could be used as a rating.

Tavakkoli et al. (2010) in another study developed a fuzzy logic based model to help investors assess the financial performance of companies and rank the companies operating in the drugs and health industry. They selected the value drivers based on factor analysis and stock exchange experts' judgments.

Chen and Chiou (1999) in their research create a fuzzy based credit rating system where they used three main nodes of financial condition (FC), general management condition (GM) and characteristics and perspective (CP). In fact, in terms of using financial ratios their model has some similarities with the models used in this study. As such referred to as liquidity ratios -quick and current ratios-, financial structure ratios -such as debt ratio and long-term asset efficiency ratio-, profitability ratios -such as interest expense to net sale ratio and profit margin and return on equity- and efficiency ratio such as inventory turnover, receivable turnover and asset turnover ratio. Their research used multi-layered fuzzy structure with four layers (the models in this study have 3 layers). However, unlike models used in this study (using regression analysis in determining the importance of each value drivers) they made use of expert judgment.

Similarly in another study, Tufan and Hamarat (2003) in order to build an investment decision tool, they employed fuzzy based model and financial ratios as the fuzzy value drivers such as liquidity ratios (current ratio, quick ratios and inventory over net working capital ratio), activity ratios (inventory turnover ratio, receivable turnover ratio, networking capital turnover ratio) and financial structure ratios (such as equity to total asset ratio, long term debt to total liability ratio and some others.). They used Istanbul Stock Exchange (ISE) 100 index information for year 2002. They rated them and based on the rating they suggested to investors whether or not to buy the shares.

R.T.McIvor et al. (2004) also used fuzzy approach to support financial analysis in the corporate acquisition process. They used 3-layer fuzzy network model, similar to the models used in this study. However again, for magnitude of each value drivers they used human precedencies. The financial categories (nodes) are profitability (including gross profit margin, profit per employee), efficiency category (including return on capital employed, net asset turnover and fixed asset turnover), liquidity category (including current ratio) and financial strength category (includes gearing ratio). Their study used 50 eligible UK based companies operating in the computing sector. The results obtained from fuzzy model indicate how the corporation is eligible for corporate acquisition. Finally Jiao et al. (2007) used a fuzzy adaptive network (FAN) in combination with human judgment for designing a credit rating model for small financial enterprises. The work displays numerous similarities to this study in terms of using FAN. They employed three categories or nodes of financial conditions (including liquidity ratios, financial strength ratios, earning ability or profitability ratios), management measure and characteristic and perspective of the products as a third category.

4.4 Data

The two fuzzy network models are developed based on the two separate samples; one a sample of 218 financial institutions, which operate in 18 Asian countries over 21 years. In total 2,112 observations are on which the fuzzy scoring model for FIs is built upon and the other sample covers approximately 12,000 large corporate companies operating in 17 CIS and CEE countries over 10 years which the fuzzy rating model is built upon. However, in order to use two dimension panel model and for simplification, an average of all data belonging to each country for every year is taken in order to have the panel of countries over the years.

These data sets were used for detecting the primary determinants of profitability in chapter 2 and 3, which are used for building the two scoring/rating models in this chapter. Moreover, data is used to detect the value drivers' distribution shape in order to impose them to our scoring/rating models. Therefore, the fuzzy value drivers all bear the characteristics of the sample data.

4.5 A customised fuzzy model

In this section, building the customised fuzzy network model is explained in three main steps. Step 1 is to define the fuzzy network structure specification i.e. defining the nodes and leaves of the tree. The second step is to define the membership function attributes, which is followed by the last step of defining rules and an aggregation method, which will result in the output of the model.

4.5.1 Model specification; defining nodes and leaves of the fuzzy tree model

After the basics of the fuzzy system have been explained in the previous sections, the building process of a hierarchical fuzzy system to be used as a method for credit scoring/rating is now explained. A hierarchical fuzzy inference system or network not only provides a flexible architecture for modelling non-linear systems, but can also reduce the size of the rule base to some extent. In Figure 4.9 some possible hierarchical Takagi-Sugeno Fuzzy System (TS-FS) models for four input variables and 3 hierarchical layers are depicted. The problems in designing a hierarchical fuzzy logic system, as stated by Yuehui and Ajith (2010) includes; the selection of an appropriate hierarchical structure, the inputs for each fuzzy TS sub-model, determining the rule base for each fuzzy TS sub-model, optimising the parameters in the antecedent parts and the linear weights in the consequent parts. However, there is no direct/systematic method for designing the hierarchical TS-FS.

The proposed fuzzy tree structure models look like Figures 4.12 and 4.13. There are three layers in these models. As anticipated, the value drivers do not affect the final output directly. These are summarised into different layer groups forming intermediate variables (nodes) until the final scoring/rating is reached. The approach is then modular and gives rise to a conceptual map, an evaluation tree that is run from nodes to trunk. In the modular approach followed, each vector is transformed into a vector having fewer components: this means that the variables have been grouped to generate intermediate variables. Conceptually, the scoring of an FI then depends on the combination of the two variables of financial efficiency of FIs and the country macroeconomics. The rating of a firm depends on firms' financial efficiency, country macroeconomic environment, as well as the special situation of countries in transition, which are privatisation indexes. Based on the literature and regression analysis, the fuzzy model structure is defined. Looking at the model, credit rating depends on the company's financial situation and the country where the company operates in. Essentially, ROA was selected as the index for credit rating and the value divers were grouped into two or three nodes to decrease the number of rules generated. Moreover, there was an effort to avoid including qualitative factors such as the age of a company. As such, value drivers are subjective and their influence on the output needs to be defined by expert judgment. Nine value drivers of profitability (ROA) are already defined by regression analysis. However, in order to decrease the number of rules to be generated and also ensure that the model is not overly complicated, four value drivers including cost of employee (similar to the Jiao et al. (2007)), ROA (similar to the Jiao et al. (2007)), NWC turnover, credit period (similar to the Jiao et al. (2007)) and ICR as *efficiency* node were grouped. The macro-economic value drivers of GDP and inflation as macro-economic node were grouped. Other than these two, there were two other value drivers which were specifically for the countries with economies undergoing transition; those variables were asset share of foreign banks as percentage of GDP and market capitalisation. These ratios also grouped in a node called privatisation and affect the credit company rating.

In case of credit scoring model for FIs, similarly, there are two nodes: one is the financial efficiency of FIs and the other is macroeconomic environment.

Emphasising again, if only 9 or 8 leaves connecting directly to the model's output were used, a large numbers of generated rules would have been produced which make the model very complicated and slow its performance[19].

This study aims to highlight the fact that risk modelling is a combination of art and intelligence; therefore, designing the model, selecting categories and variables are all a result of the model designer's abilities. The advantages of using fuzzy techniques over regression models are: a) the ability to compare the company among all companies in terms of an specific value driver as in fuzzy the minimum and maximum of each value driver is defined and the value of a driver belonging to a specific company falls between this minimum and maximum. However, in regression analysis, no such opportunity exists and a precise and "solid" result is obtained. b) In any regression analysis, only mean and variance are considered, however, in fuzzy membership functions, median is also considered which shows the skewness of each value driver. c) In regression analysis, the crisp coefficient of the value drivers are multiplied by the real value of an specific variable and then summed up to obtain the output. However, in fuzzy a non-crisp area exists, the value of the value driver is not precise and crisp and has a degree of being low, medium and high, meaning smoothing.

4.5.2 Defining fuzzy membership functions: fuzzification

For derivation of fuzzy sets, one may use three different methods, namely: a) voting by multiple experts; a fuzzy set's membership function can be based on cumulative frequency of votes by experts e.g. membership value of 170 cm is tall, determined by how many of them regard 170cm as being tall. b) Statistical analysis of domain

[19] In addition, as much as the number of variables and number of membership functions are increasing, the number of rules produced also need to be increased and the more complicated the model will be in terms of interaction between variables and understanding the designed model. Therefore, consideration of the parsimony of variables is required to ensure that the model is kept simple, with a low number of variables and not add so many unnecessary interactions between variables. With the shown model structure, 747 rules were created.

data; for example, data is normally distributed; mean and standard deviation are known. However, data in financial analysis, marketing, risk assessment, project management and so on are seldom normally distributed and can be subject to sudden changes. c) data mining techniques which are used to decompose underlying variables into arbitrary collections of fuzzy set.

In this study, the second method is used. Through employing the statistical analysis it is possible to derive the shape of each derives. In defining of fuzzy sets[20], no formal procedure for designing these functions exists. The fuzzy sets are usually trapezoidal or triangular; however, bell-shaped fuzzy sets may also be used instead of triangles. Sigmoids (S-curves) and linear surfaces are also used in information systems and are applied in social sciences. In this study, based on the distribution shape of the data set for each value driver, different kind of membership functions are used and illustrated in Annexure C.1. For defining the MF there are three sub-steps.

Sub-step 1; Extracting the minimum and maximum of each financial ratios or membership ranges Using the two separate databases, the range of each value drivers are defined [21] as shown in Figure 4.11 where the minimum and maximum of each value driver is set based on historical data sets. As can be seen, the credit period, which is defined as days, have the minimum of zero and maximum of 685 days in the pruned data set. X-axis defines the ranges cover all the value drivers.

The approach is similar to the approach of R.T.McIvor et al. (2004) which first determine the total range of all membership functions.

[20] Various types of Membership Functions are S-shaped function, Z-shaped function, Triangular Membership Function, Trapezoidal Membership Function, Gaussian Distribution Function, Bell shaped membership functions, Pi function, Vicinity function, left-right functions, Sigmoid functions which all are shown in Annexure C.1

[21] The building of the models is based on observations without missing values for any value drivers. Therefore, the ranges shown for each value drivers are different from the ranges shown for the same value drivers in previous chapters.

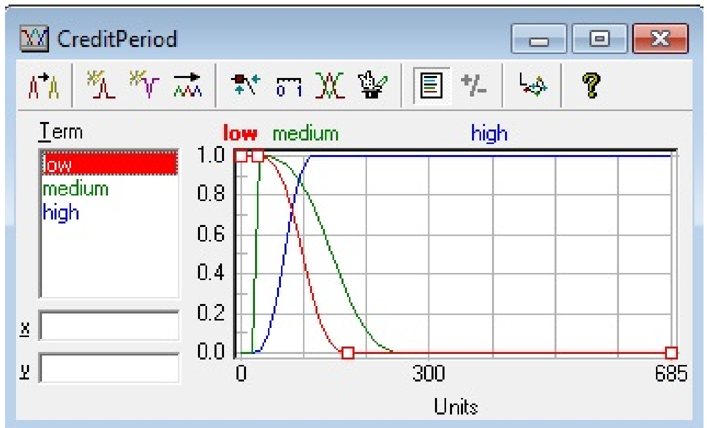


Figure 4.11: Membership function example: credit period

Sub-step 2; check whether the value drivers in the sample are dispersed evenly or unevenly via retrieving distribution shapes In this sub-step for producing more accurate results, the dispersion of variables is checked. The default membership function shape is a triangular type of membership function which is evenly dispersed. However, depending on the historical data sample used, it may deviate from this type of standard form. It may be worth mentioning that by using expert opinion, this restriction cannot be imposed to membership functions. This might be considered as another advantage of the model. Therefore, the distribution shape of the variables (using the data set) are driven and then imposed on the membership function shape. For instance, in case of credit period value driver illustrated in Figure 4.11 the data is skewed rightly. Moreover, in designing the MFs one should remember that there should be a 25% and 50% overlap between adjacent fuzzy sets.

Sub-step 3; Defining the efficient number of Membership functions The third sub-step involves the art of defining the optimum numbers of membership functions. As mentioned previously, the number of membership functions increases the number of rules to be generated also increases which follows the x^n rule where x stands for the number of variables and n stands for the number of membership functions. In addition, it depends on the capability of fuzzy model generator software that is used. There is a restriction on maximum number of rules generated for each software. For instance, the FuzzyTech student version has such limitations. Therefore, three-membership functions were used for the input, intermediate value drivers and for output variable 11 MF are used for accuracy, this is shown in Appendix C.3.1 and Appendix C.3.2.

4.5.3 Defining the value drivers influence on the output

This sub-step is extremely crucial and important and has much impact on the ultimate results. In this step, in order to define the consequence parameters for the value drivers, their obtained significance is used via regression analysis and mapping them via linear equation to nodes and value drivers weights. Moreover, during this step, one should decide the inference method - either Mamdani and Sugeno are to be used. The Sugeno type of inference engine is preferred to be used since it produces numeric values instead of fuzzy output. The model is based on sets of rules defines in form of IF-THEN rules through defining the impact of each value drivers on the output variables. The rules are defined considering the influence of each variable on the output, which is credit risk. For instance, it is estimated through a statistical model, GDP growth has a positive influence on country risk, which leads to increase in corporate rating. The influence of value drivers in each node is summed to 100% illustrated in Figure 4.14 and 4.15. For instance, it can be seen in the Figure 4.15, that efficiency has 70% and macro-economic has 30% weight.

The model structure uses three layers. The two designed models are illustrated in Figure 4.12 and Figure 4.13. Moreover, as shown in Figure 4.14 and Figure 4.15 by using simple mapping, the influence of each value driver on the next node was obtained. However, it is important to note that the summation of the absolute weights for the value drivers, which grouped together, is equal to 1 for each layer. These percentages reflect the important (coefficient) of each value driver in the regression models.

4.6 Results

This section reviews the results of the two designed models, one for financial institutions in 18 Asian countries and one for very large corporations in 17 CIS and CEE countries. Figure 4.18 and Figure 4.19 shows the two final models.

First, the similarities of these two models are explained and then the focus is shifted towards their differences. The two models have three layers which comprise of input value drivers (the first layer), intermediate variables (middle layer) followed by the output variable which is the last layer. The membership functions for all the value drivers (input variables) are retrieved from their data set distribution. It means that whatever the shape of value driver distribution is, it is imposed to its membership function shape. See Appendix C.3.1 and Appendix C.3.2 for Fuzzy documentation. Also important is to address the differences which exist between the two models. In the scoring model for financial institutions, the two main factors are financial efficiency of the FI and the other being the macro-economic environment in which the financial institution operates. The difference existing between FI scoring model and corporation rating model is due to privatisation node. This is because the sample of companies are from CIS and CEE countries, where privatisation is relatively new and has major impact on the performance of companies. The final output is the aggregation of all three factors which result in to a rating or scoring of the credit customer.

The method in which fuzzy system processes the financial and macroeconomic categories is represented in Figure 4.12 and Figure 4.13, the scaled financial and macroeconomic ratios are used as inputs to the fuzzy system and the output is single number between 0 and 1 or 0 and 100 that represent the aggregation and de-fuzzification of the inputs. The fuzzy system calculates a single crisp output for each of the companies in the database. The results show the output from the intermediate fuzzy systems. In the model for corporations, these intermediate fuzzy systems are three categories, which are efficiency, macro-economic environment and privatisation, and for the FI scoring model, there are two categories, which include financial efficiency and macro-economic environment. As mentioned previously, the extra fuzzy system in corporate rating model is due to specialty in the data for CIS and CEE countries - where privatisation has an important role for the credit rating of corporations. The results of the two scoring/rating model are shown in graphical form (Figure 4.16 and Figure 4.17) so that comparison of results can be easily undertaken. As seen in the graphs, the range of scoring for 180 FIs are between 0 and 100 and ratings for 500 corporations are between 0.20 and 0.55. The system enable ratios of higher importance to have greater influence over the output but not to the extent that a high priority ratio can fully determine the output. The average is used to determine the position of the all the membership functions therefore a company's position, in relation to the average ratio will determine which membership functions it falls under.

As stated by Magni et al. (2006) "this kind of analysis may be accomplished for various purposes; financial analysts may adopt it for ranking firms belonging to a particular industry, or shareholders may use it for rewarding managers or as an incentive tool. Managers themselves may perform the analysis to understand whether a particular decision increases or decreases the value-creation power of the firm."

In addition, following the completion of the model, the user is able to make one or some of the variables inactive if they think that the value driver at that moment does not add any value to explain the output. For example, if the portfolio comprises of credit customers in one country, there is no need for considering the macro-economic and privatisation effects and these factors may be deactivated.

TThe method in which value drivers (input variables) determine the scoring/rating is modular: They affect intermediate variables, which in turn determine the final scoring/rating. The modular approach therefore, consists of grouping the variables in modules which are then grouped in higher-level modules progressively narrowing the number of variables involved until only one variable (the output) is left (see (Magni et al., 2006) for similar approach). The corporate model incorporates 9 value drivers or variables (all of which are considered quantitative), 3 intermediate variables, 4 rule blocks, 47 membership functions and 288 fuzzy rules. The FI model comprises of eight value drivers, two intermediate variables and 3 rule blocks, 39 membership functions and 144 fuzzy rules.

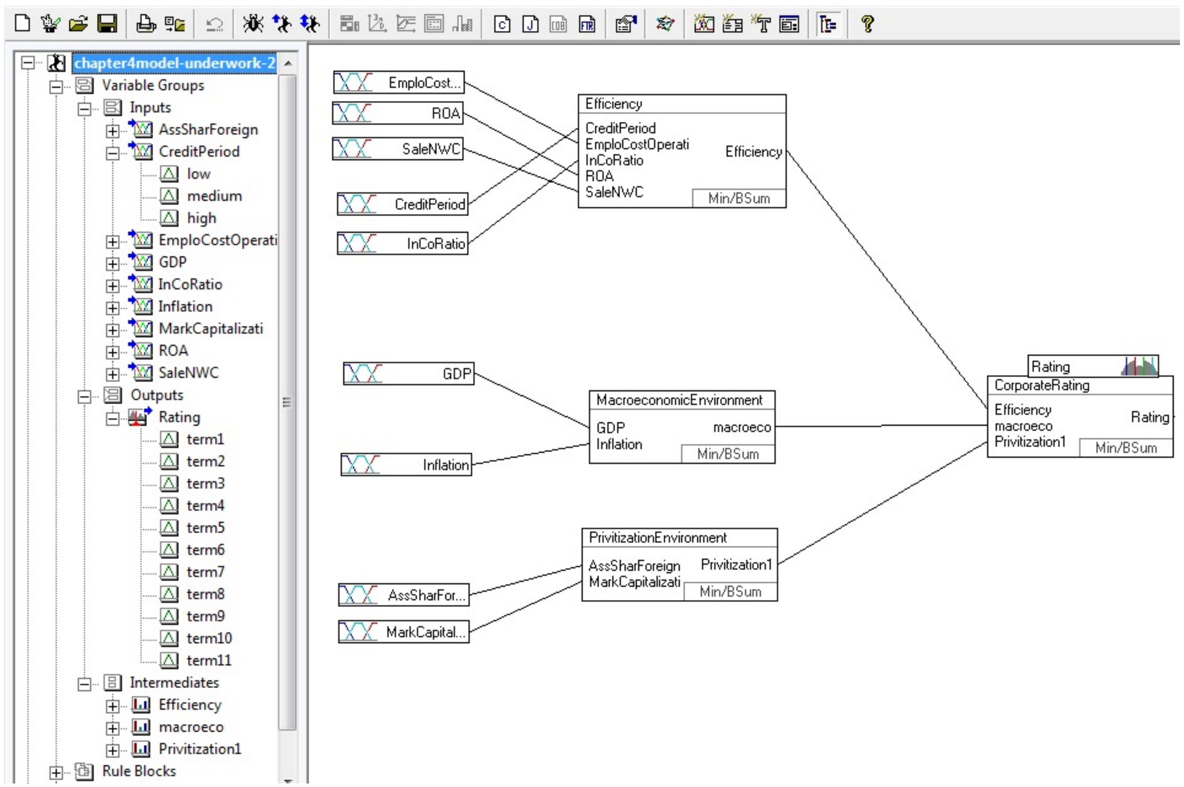


Figure 4.12: Proposed fuzzy network structure for corporate customers

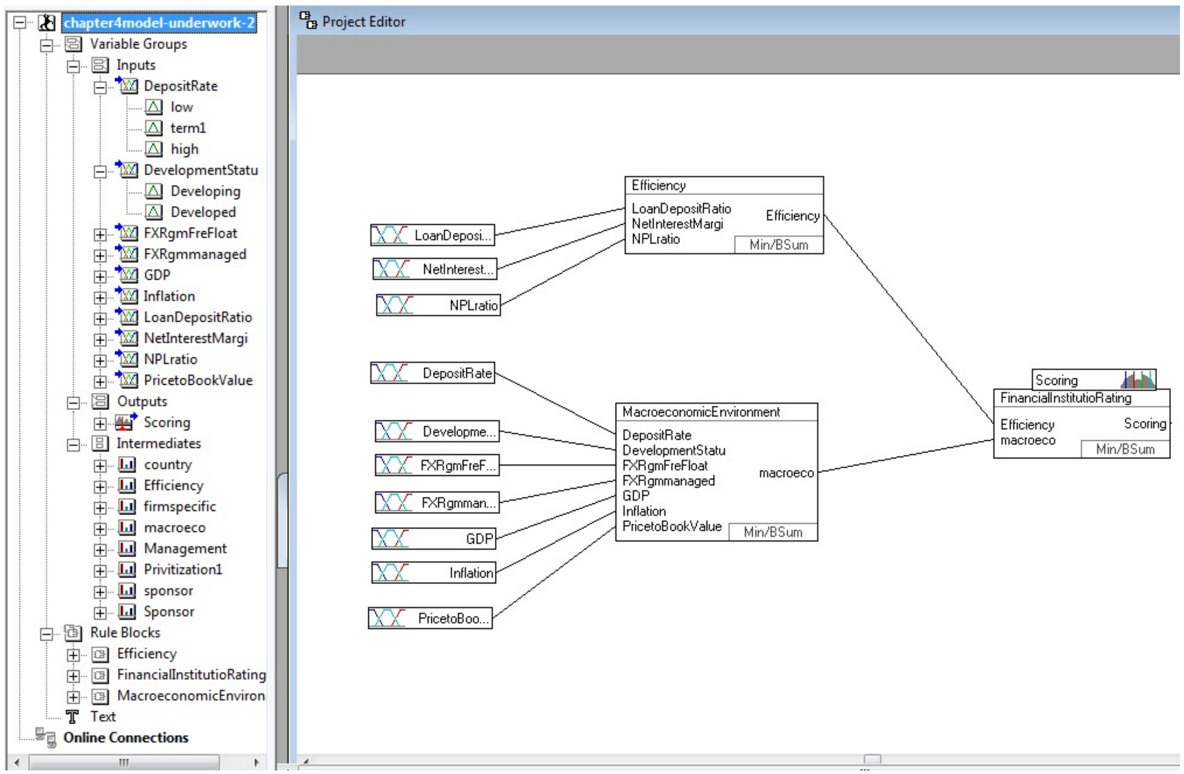


Figure 4.13: Proposed fuzzy network structure for financial institutions

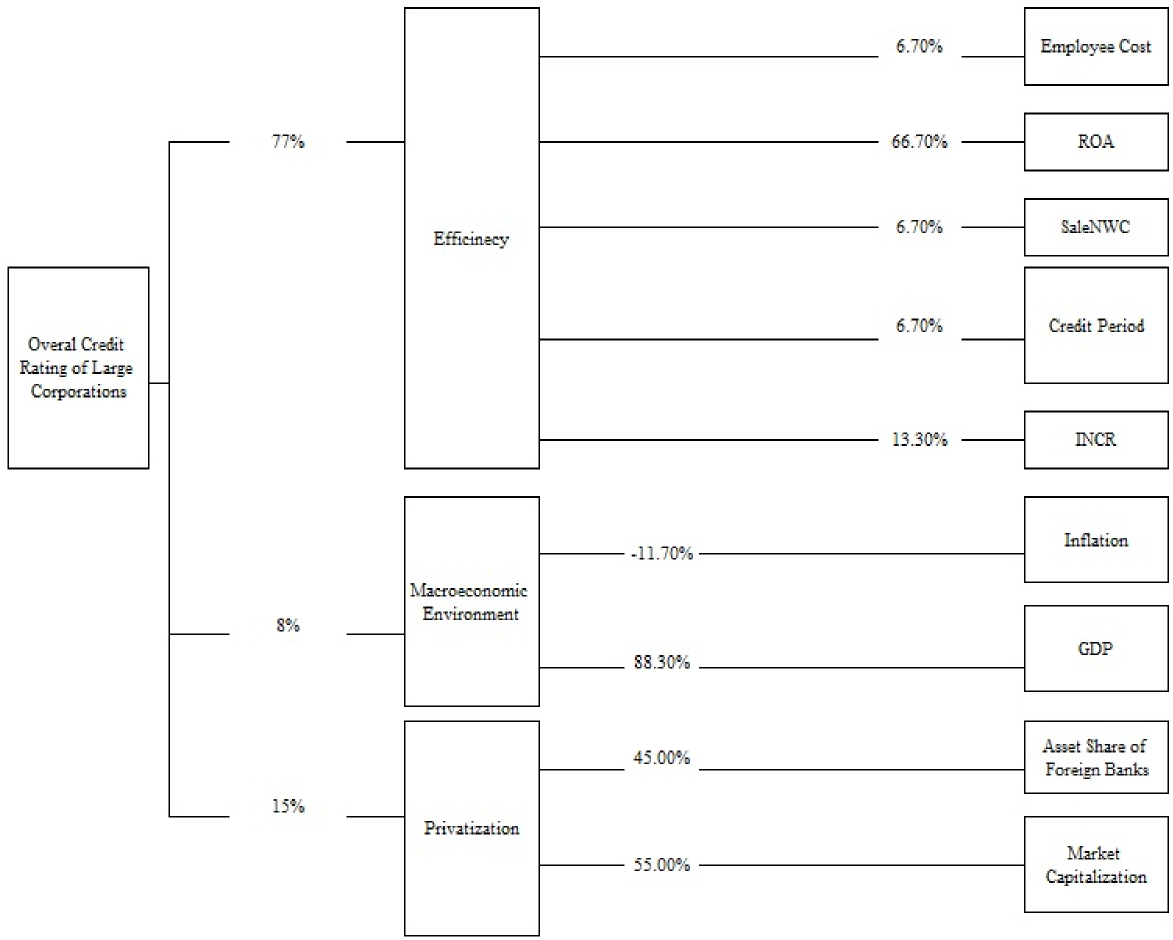


Figure 4.14: Corporate model: fuzzy network structure

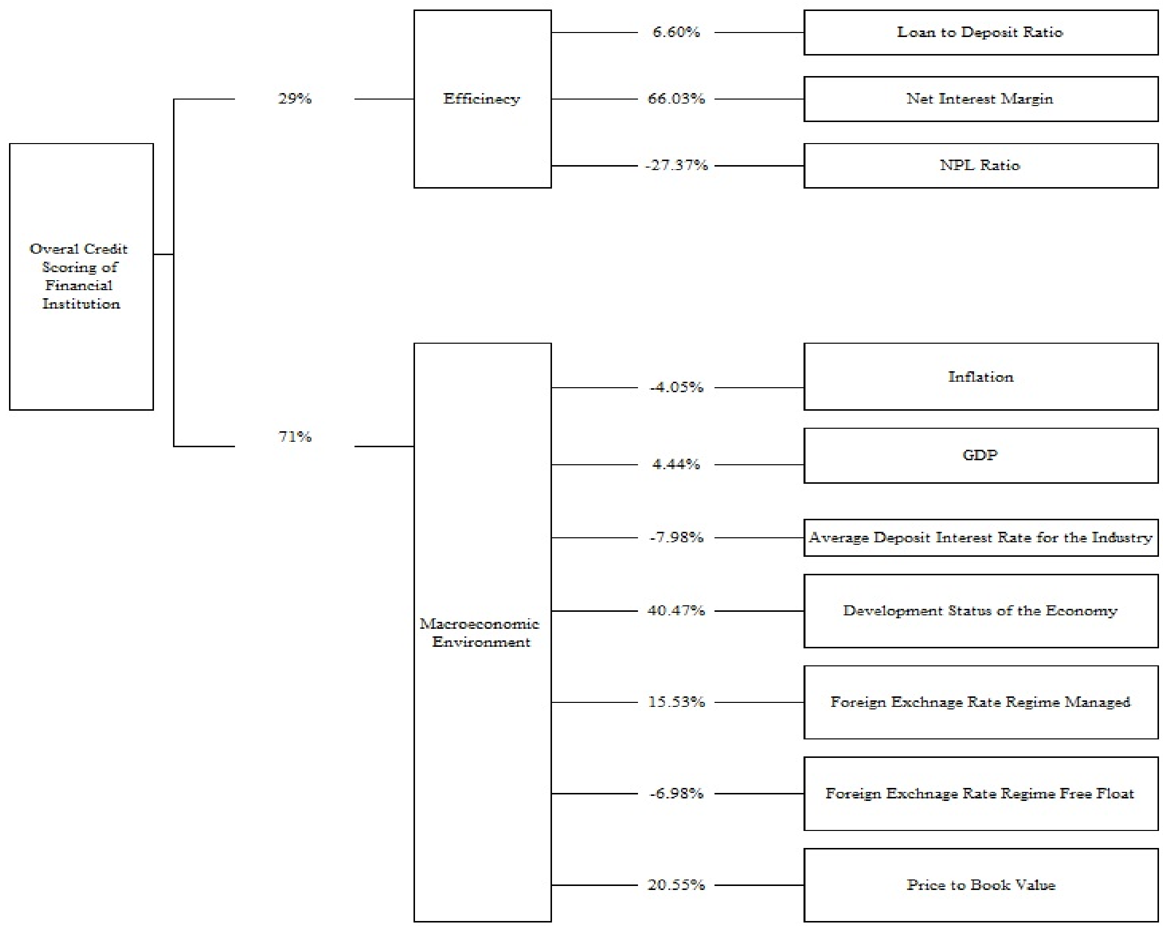


Figure 4.15: FI model: fuzzy network structure

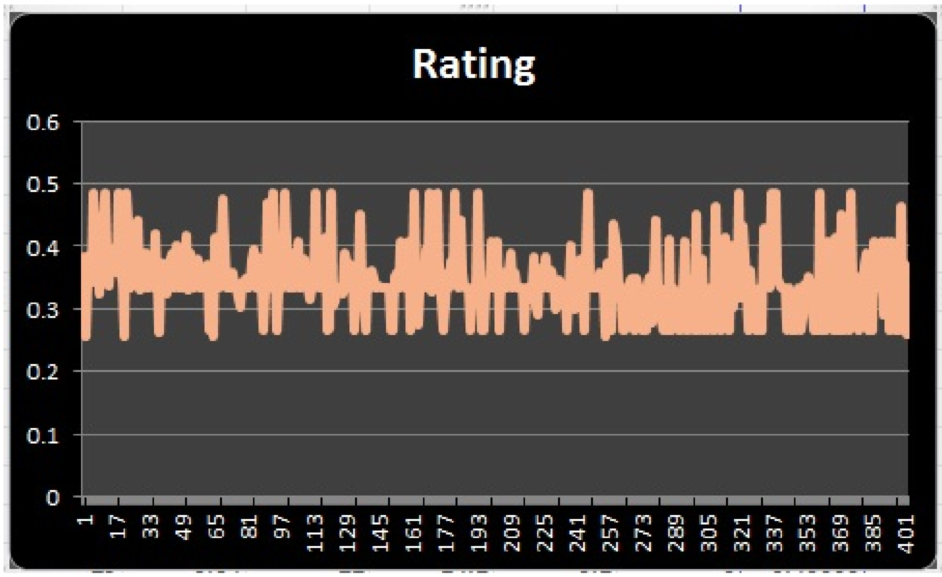


Figure 4.16: Rating results for 403 companies

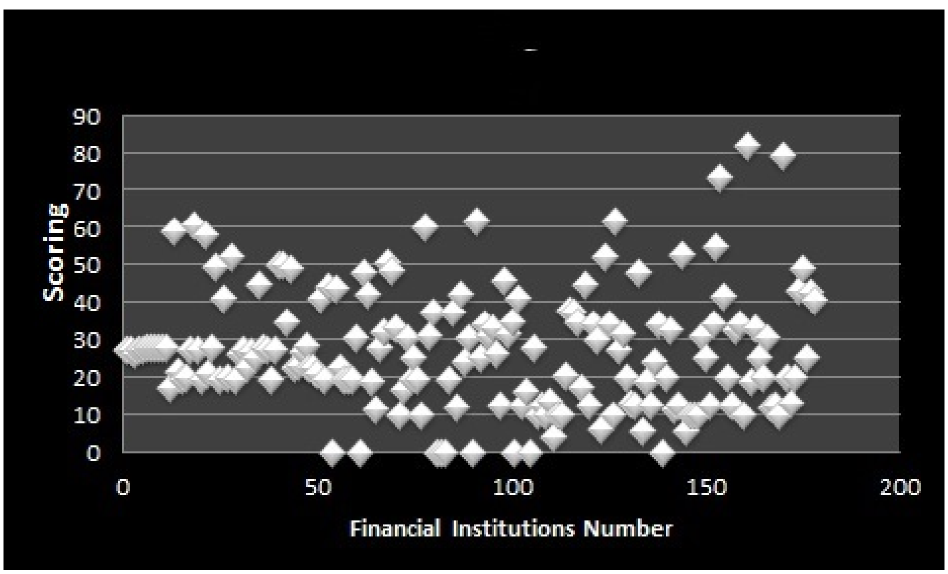


Figure 4.17: Scoring results for 180 financial institutions

4.6.1 Sensitivity analysis

In Figure 4.18 and Figure 4.19 below is shown a screen-shot of interactive recalculation window (in the process of work within program). The user enters (on the left) the numerical value (evaluation) of input parameters and (on the middle) program displays the result of calculation of (there is only one output variable) output parameters. On the right side, changes in the intermediate variables exist where it is possible to monitor the impact of input variables on these variables.

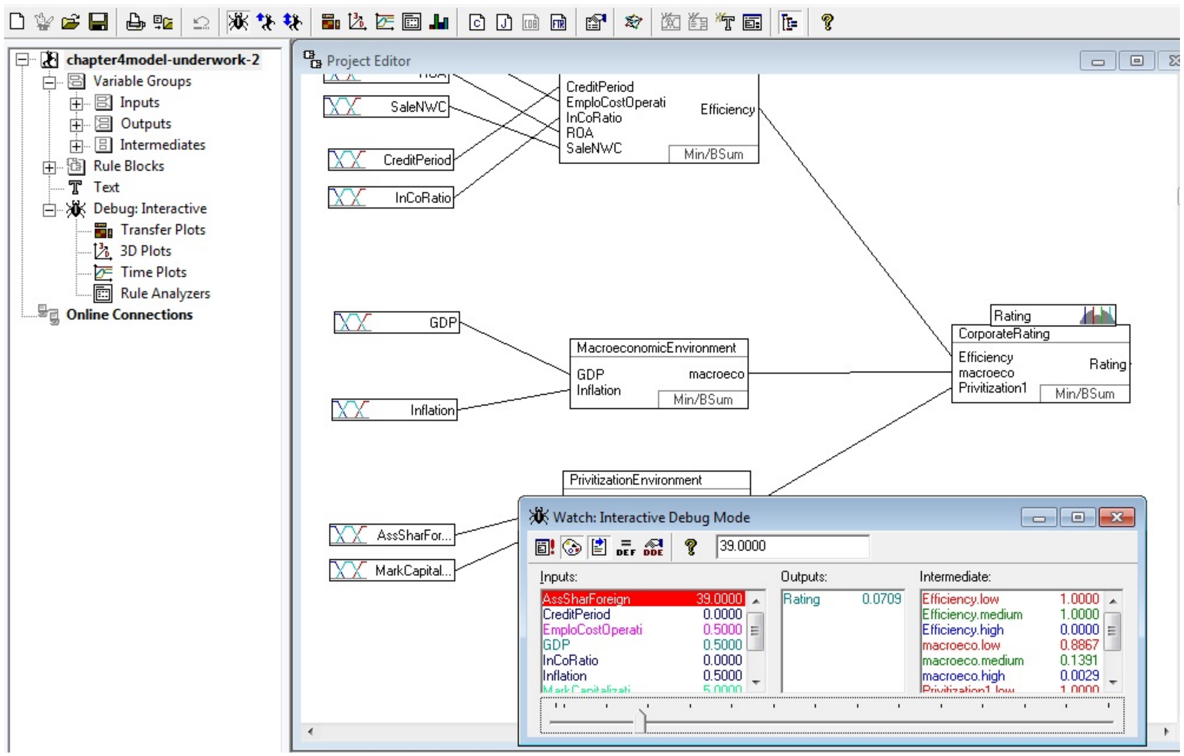


Figure 4.18: Corporation model interactive panel

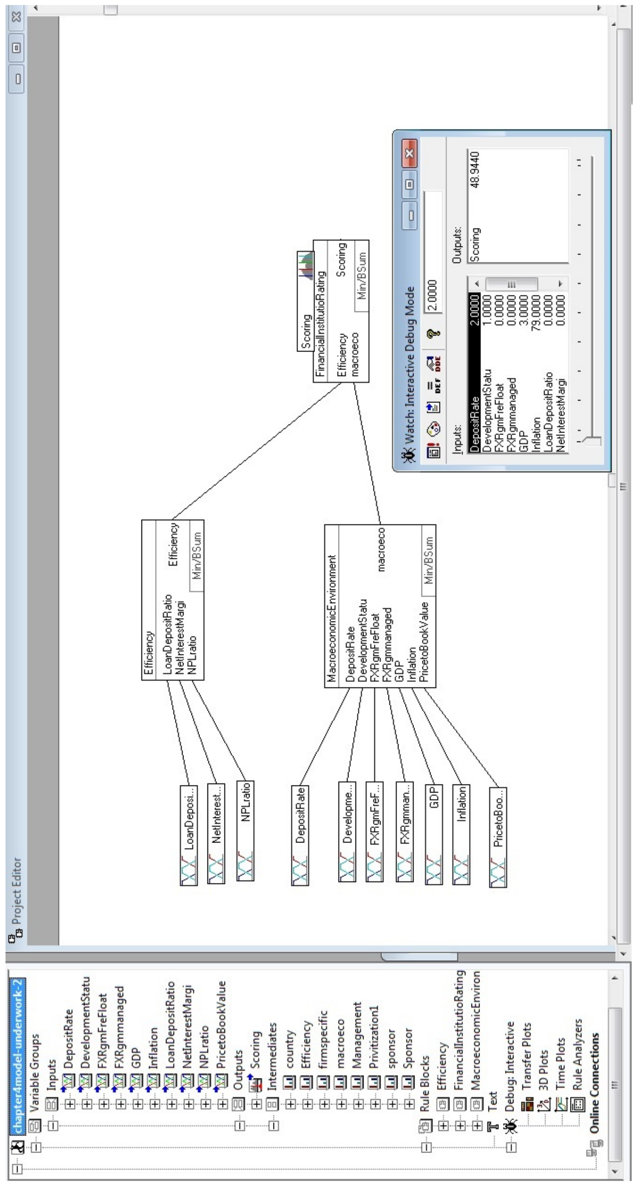


Figure 4.19: FI model interactive panel

4.6.2 Robustness analysis

For testing the reliability of the desired models, two different ways have been selected. In order to validate the designed corporate rating model, capital market data has been made use of and the results are shown in the Table 4.2, indicating a negative correlation between the P/Earning and P/B ratios and the rating results. For undertaking this, the correlation test was used. The results show almost 40% negative correlation. As stated by Shen and Yan (2010), Fama and French (1992) both in academic and pre-critical fields, firms that have higher ratio of book to market equity (b/M) are often classified as value stocks.

For testing the scoring model for financial institutions, another method is used which compares the scoring result with the credit rating result of an external rating agency. In this regard, Capital Intelligence ratings are selected for the scored financial institutions. The Table 4.3 shows the result in the column and the row shows the CI results.

	rating	pehigh	pbclose	pblow	pbhigh	pbaver~e	pbcurr~t
rating	1.0000						
pehigh	-0.1248	1.0000					
pbclose	-0.2775	0.2230	1.0000				
pblow	-0.3685	0.2879	0.7092	1.0000			
pbhigh	-0.2872	0.2403	0.8955	0.6430	1.0000		
pbaverage	-0.3736	0.2968	0.8241	0.9720	0.8048	1.0000	
pbcurrent	-0.2460	0.1190	0.6352	0.5477	0.4904	0.5748	1.0000

Table 4.2: Correlation between the rating model results for companies and capital market data

Scoring/CI-Rating	A	B	c
0-25	**23.33%**	**40.00%**	**100.00%**
26-60	**76.67%**	**60.00%**	**0.00%**

Table 4.3: Comparison of FI Scoring Results with CI Rating Results

This table shows that 100% of the companies that are rated as low by the model are also rated as C by CI. 76% of the top rated customers by the model are also rated as A by CI. The results of middle rated companies are mixed.

4.6.3 From scoring/rating to limit setting, pricing and provisioning

The value provided by the fuzzy model which is an score between 0 to 100[22] can be used for limit setting. For this reason, the scoring/rating needs to be divided into several categories. For instance, one can simply divide it into five categories where each category implies different levels of credit risk. For example, one may stipulate that firms in interval [0, 20] have a high credit risk, firms in the interval [20, 40] are mediocre and firms in the interval [40,60] possess a high level of risk. This use of the model may provide analysers with more helpful information.

This basis can be used to assign limits to short-listed credit customers and set a risk base pricing, accordingly[23]. This seems logical since credit customers with high level of credit risk should be offered less credit limits and high loan pricing[24].

The risk base limit setting is very much applicable for defining the credit limit for financial institutions acting as intermediaries of MDBs rather than for corporate customers. Because in defining the limit for corporations, the capacity of the firm to absorb the fund and its ability to repay it in a timely manner is an important issue, which the model in this study did not take it into, account and is not part of the model objectives.

The other application of these designed models includes calculating the adequate risk base loan loss provisions to safe guard the bank against possible default of the corporations, as well as financial institutions, acting as the bank's financial intermediaries. In this

[22]Higher scores indicate lower risk.

[23]An important component in the management of a single client's credit risk is estimating the accurate pricing for every single customer which this pricing should cover the expected cost that the financial institution has to carry when the transaction is agreed upon, as well as the refinancing costs and the risk premium, i.e. the expected loss of trade and the costs of provisions for the unexpected loss (Uwe, 2003).

[24]Normally in price setting there are three major components, the base rate which can be a EUROBOR or LIBOUR (which is the opportunity cost of the Bank' s money), the operational cost of the bank and the risk margin component (which is calculated by taking into consideration the risks inherent in the transaction).

case, similar to pricing, one can use the mapping process to define appropriate loan loss provision amount for the credit customers in our portfolio. Moreover, geometric progression for mapping formula is proposed.

Periodic publication of the rating of firms sheds light on the firm's power of generating value in the future and assists investors to make decisions that are more rational. In case of MDBs it helps to monitor the credit portfolio risk profile. Moreover, this kind of scoring/rating could represent a tool, which adds to the information provided by current rating agencies and financial analysts. The scoring/rating and map can be used to retain the suitable credit limit for lending activities. For instance, customers with 0.4 values and above can be considered for lending activities (the customer with a value of 0.4 and below is not eligible for lending). After lending activities, this scoring/rating can also be used for asset classification and ensuring appropriate risk based loan loss provisions. Instead of mapping in this way, another output in our model can also be defined, which will link the value drivers to pricing. However, since not all customers will be eligible to pass the pricing step, the program firstly should be able to recognise eligible customers and then pass them on to the pricing step. Therefore, there is a need for further programming and this is not included within the scope of this study. The process requires more time and effort and can be left for future research.

4.6.4 Conclusion and future developments

Successful and effective risk management requires a clear understanding of the risks faced by projects and businesses. Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification and decision analysis. Due to its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modelling, fuzzy associative memory, fuzzy logic controllers and simply (and ambiguously) fuzzy systems.

In this study, despite the usual fuzzy system using the expert system replicating the reasoning of a human expert (or experts' panel), historical data and data mining techniques for designing the fuzzy models were used. Subjects interested in this type of a tool include rating agencies, financial analysts, investors (shareholders, bondholders), banks and managers. The field of application of such an expert system is manifold: it is an evaluation technique, as well as a corporate governance tool and a device for assessing the increase in value associated to particular decisions. The fuzzy expert system proposed in this work is an alternative to the decision models and evaluation models, which exist in literature.

As reported by Magni et al. (2006) financial economics offers elegant models for use, such as discounted cash flow methods which, though widely used, do not rely on explicit analysis of all drivers at play (Magni et al., 2006). The evaluation of a firm is then grounded on computations of cash flows whose magnitude is often arbitrary. In a sense, the DCF methodology only helps in the final step (discounting cash flows with a risk-adjusted rate of return), and does not inform one on how many and which value drivers are taken into account. Nor how they have been aggregated and nor their direct or indirect financial impact are specified.

When other formally flawless models are used, e.g. options theory or dynamic programming, they seem to be mathematically complex and not intuitive, and, admittedly, "managers do not have the necessary mathematical skills to implement or even understand it" as stated by Magni et al. (2006). Furthermore, they are capable of dealing only with a very limited number of variables (usually one) and require unrealistic assumptions, which are highly simplified for mathematical tractability, so that the result is that of shunting aside reality. On the contrary, business economics seems to suggest an opposing point of view: the reality is overly complex that it is impossible to formalise or even rationalise the situation on hand. When an attempt is made to search for some drivers influencing the value of an economic activity (and consequently, the solution of the decision process) this is accomplished in an informal way by attempting to guess the drivers but omitting to offer a model that connects them. Looking at the positive side of these two disciplines, one may note that finance suggests that there is a need for formal models for better description and rationalisation of the evaluation process, while business economics suggests us that reality cannot be described by merely resting on mathematical models, complex in their application and simplified in their assumptions. Therefore, this research proposes a model, which seems to meet both requirements. Data mining techniques and fuzzy logic, combined together, seem to be an interesting tool for valuing firms. Moreover, fuzzy logic models have an inherent advantage because of their ability to account for fuzziness or ambiguity in the system. Other advantages include the relative ease in interpretability and its integration with other systems such as neural networks for greater accuracy.

The approach offered here is easy to understand and easy to implement. In addition, it does not require advanced knowledge of mathematics and does not make any particular assumption on the variables affecting the output value. The solution derives from logical implications (the "if-then" rules), therefore anyone is able to understand and construct them. At the same time, there is a formal model, which rationalises the evaluation process, and automatically gives provides the final value. As Magni et al. (2006) states fuzzy logic is in this sense, a useful tool for describing the value of a firm, since the complexity (by designing a fuzzy network model) of real-life situations is handled through "vague" variables and "vague" interactions, which better replicates the human mind, as well as economic phenomena. The mental processes of human beings are in reality, imperfect and imprecise, and individuals often act in contexts of incomplete (and unclear) information. No individual is able to formulate precisely all possible solutions of the decision-making process and the corresponding consequences. It can be stated that this study has shown that the through "vague" connections accomplished by constructing the fuzzy system, adequately replicate such imprecision and imperfectness.

Magni et al. (2006) also emphasise that a fuzzy approach, unlike classical ones, seems to be capable of integrating qualitative and quantitative analysis, so that the model is not forced to limit its scope to numerical variables with well-specified units of measures but can handle any type of qualitative drivers (which is an impossible task for classical mathematics). Furthermore, it is possible to handle a high number of value drivers, simplifying the design of the whole system, dramatically reducing its complexity and intelligibility: the system is modular, therefore not explosive, since it is run from nodes to trunk. As a result, one can shape the problem to take explicit consideration of business, strategic, organisational and financial aspects. Finally, the system is extremely flexible; one can deactivate any value driver in the model, introduce numerous additional value drivers and change the rules connecting drivers and intermediate variables at any point.

It is important to note that no tailored model is free from deficiencies. An attempt was made that only quantitative value drivers were included in the models. Also, the models were kept as "simple" as possible and understandable and easy to implement. The models used in this study do not require advanced knowledge of mathematics and do not make any particular assumption on the value drivers affecting the credit risk scoring/rating. However, the research may have missed other important qualitative factors, thus future investigation will concentrate on adding more value drivers as well as obtaining feedback from the user and the system and attempt to improve system performance. The solution derives from logical if-then rules so any one can understand them and conduct them. Moreover, the model does not have the limitation that regression models present. One is able to combine this fuzzy network model with decision tree type of models where some value drivers can play critical role in stopping the scoring/rating process if one or several pre-requirements are not met[25]. The class of target groups, which may be interested in such models, are rating agencies, financial analysts, investors (shareholders, bond-

[25]similar to the study of Janikow (1998).

holders), banks and managers. It may be particularly useful for loan pricing purposes, rewarding and compensating managers and finally, helping decision makers in selling or buying shares.

Chapter 5

Conclusion

Risk management becomes essential and an integral part of daily activities in modern life. This is important for us as individuals when a choice needs to made between several investment opportunities and this is more essential for lenders such as commercial banks, investment banks etc. who need to decide about their lending opportunities swiftly, before their competitors (other lenders) act more quickly to undertake the credit investment. It is essential for them to evaluate the credit proposals in order to select ones with lower risks. Although, plenty of credit risk scoring/rating models exist for calculating the probability of default for credit customers. As such referred to as standard statistical models (e.g. logit-probit models) and market based models (e.g. call option models), where the event of default is defined as the time when the market value of assets fall below the market value of liabilities. The later models have their own drawbacks. Therefore, there are still lacks for models in order to calculate the default probability of FIs and unrated corporations specially whenever the default history is very low or either does not exist. This is the requirement for MDBs who have such customers in their credit portfolio. They need to select the low risk credit customers and they need to offer those selected customers the risk based pricing. In addition, after financing them, to keep adequate loan loss, provisioning is required according to their risk level. In this study, the focus was evaluation of Multilateral Development Banks' credit customers who are mostly large corporations and financial institutions (where the risk calculation method for them requires significant development). Therefore, in the first two chapters, an attempt to determine the key profitability determinants (as index for the firm financial soundness) factors was made which was followed by their employment to design two separate credit scoring/rating models.

5.1 Main findings and policy implications

Chapter 2 investigates the main determinants of profitability for financial institutions. As the profitability of banks is the most important indicator of FIs' financial health and credit worthiness, it is employed and its main determinants for assessing the financial stability of FIs. This is due to the fact that a decrease in profitability and recurrence of loss is the major factor which leads to depletion of FIs capital. In this regard multilevel models (two-way panel model) have been used to test the relation between the level of financial institution profitability and different sets of variables ranges from financial institutions specific variables to banking industry and macro-economic variables. The framework provides both the methodological as well as empirical upgrade of the profitability determinants as a result of using MLWIN software application. This could successfully handle a three dimension/two way panel model by employing strong unbalanced data set in order to detect the determinants of profitability for FIs in 18 Asian countries (all are borrowing members of Asian Development Bank) and over a long period of time. The results indicate that, the profitability of FIs is greatly influenced by their country's macro-economic environment, banking industry and by the level of risks inherent in the institutions. The results show that net interest margin as proxy of efficiency, non-performing loan to loans as proxy of asset quality, loan to deposit ratio as proxy of liquidity, price book value per share as proxy of sensitivity to market has significant impact on profitability, which all represent bank specific variables. For industry specific impacts, industry deposit interest rate were employed which shows to have significant impact on the profitability of banks. The other sets of variables, such as GDP growth rate and inflation rate, which represent macro-economic variables, show a strong impact on the profitability of the banks. All these detected variables' impacts are compatible with existing theories. Moreover, the study has defined and tested some new dummy variables such as exchange rate regime type, as well as the development status of the economy on profitability. The results show that countries with a free float exchange rate regime are exposed to more volatility in profitability. The findings of this study have considerable policy relevance since the identification of profitability drivers can help make forecasts on the future financial status of FIs by using forecasted macro-economic, banking industry data and FIs budgeted financial statements. Such models can play a role of a dynamic system for FIs assessment and help detect their financial fragility before occurrence. The results of this research may also be used in asset classifications. Future research can attempt to test and include governance variables such as taxation, existence of interest rate distortions, dual interest rates, multiple currencies in use, multiple exchange rate practices, parallel FX markets, balance of payments, foreign debts, maturity structure of debts, public sector deficit, fiscal and monetary policy, transparency of legislative regulatory bodies, quality of governance and regulation indicators, as well as indicators of the quality of services offered. Moreover, different size of financial institutions e.g. small, medium and large banks, types of financial institutions e.g. commercial, investment, specialized, development banks and structural shock dummy variables e.g. pre-crises, crises, and post crises can also be modelled employing different methodologies, such as dynamic panel models. Chapter 3 estimates the determinants of profitability, this time for corporate entities. Similar to the previous chapter, where profitability is used as the most important indicator of the financial soundness of firms as well as credit worthiness, in this chapter, one-way panel data set of very large corporation operating in 17 CEE and CIS European countries over a 10 year period (2003-2012) is employed. With the help of STATA statistical package, it is possible to handle two-dimensional panel data set employing dynamic panel analysis and shows that the profitability of large corporations is highly influenced by the country's macro-environment and the internal corporate governance practices of firms. For instance, past year profitability, account payable, interest coverage ratio, GDP growth, stock market capitalisation, existence of foreign owned banks in the economy have major positive impact on the profitability of firms while employee cost to operating cost and inflation have major negative impacts. This chapter also has considerable policy relevance, as it is possible to predict the boom or fall for firms when economists/policy makers play with critical macro-economic factors. For instance, when the economy has been opened to foreign banks, it brings more competition in the local banking sector or when the stock exchange market is made more efficient, one can expect more profitability for corporations. This will subsequently result in more GDP growth for the economy.

In Chapter 4, two separate credit scoring/rating models have been designed based on the fuzzy logic approach using the obtained empirical results from chapter 2 and chapter 3. To achieve more accuracy and minimise criticism, no qualitative and expert judgment based factors were used. This ensures that the models are simple and have a limited number of value drivers. Value drivers were grouped in two or three intermediate value drivers to decrease the numbers of fuzzy rules to be generated. Three membership functions were used for input and intermediate value drivers and 11 MF for output value driver for accuracy. The result for each corporation is a rating between 0 and 1 and for each FI there is a score between 0 and 100. Furthermore, the results were tested with CI rating agencies results and stock market performance data, which shows strong compatibility. Overall, this study seeks to highlight the importance of macro-economic, industry and corporate governance on economic entities (banks, financial institutions or corporations) and attempts to employ them to design credit scoring/rating models.

5.2 Directions for future research

The overall goal of this study was to provide deeper understanding in designing credit risk models. Both the scoring/rating models are based on data mining techniques (regression models) and fuzzy concepts. However, all modelling exercises (either empirical or theoretical nature) being simplified from reality are open to several caveats. As such, the research has limitations. In this final section, a critical reflection on some of these limitations is undertaken in attempt to formulate ideas for future research.

Empirical Evidence In chapter 2 where an attempt to determine the profitability of FIs by carefully monitoring the estimation steps and by considering the research question from slightly different angles was undertaken, the multilevel estimation could easily be extended by adding data from more countries. One could test for latent variables and structural break of 2007 financial crises. In chapter 3 one could use the original data format of three dimension (instead of simplifying to two dimension) as well as using data for more countries. In chapter 4, one can add qualitative value drivers using expert judgments. In general, one can design a uniform or universal scoring/rating model (employing the data for all types of customers) which is suitable for analysing a specific type of customer in a specific country by employing decision tree to move from one step to another and short list the proposals.

Regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables. However this can lead to illusions or false relationships, so caution is advisable;[1] for example, correlation does not imply causation.

Appendix A

Appendix Introduction

A.1 Balance Sheet of two main MDBs

STATEMENT OF FINANCIAL POSITION

At 31 December 2012

Presented in thousands of EUR	Note	2012	2011
Assets			
Cash and cash equivalents	25	18,227	11,888
Debt investment securities:			
Available-for-sale	12,13	17,963	26,528
Held-to-maturity	13,25	182,500	114,321
Derivative financial instruments – assets	14	11,517	0
Loans	15,17	742,614	688,218
Less: deferred income	15	(6,694)	(6,913)
Less: impairment losses	11	(42,026)	(39,843)
Loans net of impairment		693,894	641,462
Equity investments available-for-sale	16,17	43,290	31,565
Other assets	18	14,677	9,588
Property and equipment	19	699	555
Intangible assets	20	816	924
Total Assets		**983,583**	**836,831**

Table A.1: Black See Development Bank Balance sheet, Asset side

ASIAN DEVELOPMENT BANK—ORDINARY CAPITAL RESOURCES
BALANCE SHEET
31 December 2012 and 2011
Expressed in Thousands of United States Dollars

A S S E T S

	2012		2011	
DUE FROM BANKS (Note C)		$ 263,441		$ 187,989
INVESTMENTS (Notes C, D, L, and P)				
Government or government-guaranteed obligations	$ 21,696,501		$ 19,156,304	
Time deposits	1,311,006		1,151,963	
Other securities	770,508	23,778,015	1,200,002	21,508,269
SECURITIES TRANSFERRED UNDER REPURCHASE AGREEMENTS (Notes D and P)		347,453		330,044
SECURITIES PURCHASED UNDER RESALE ARRANGEMENTS (Notes D and P)		333,884		395,498
LOANS OUTSTANDING (OCR-6) (Notes A, E, and P) (Including net unamortized loan origination costs of $66,044 – 2012 and $64,901 – 2011)				
Sovereign	49,937,141		47,052,649	
Nonsovereign	2,942,537		2,741,641	
	52,879,678		49,794,290	
Less—allowance for loan losses	42,533	52,837,145	35,030	49,759,260
EQUITY INVESTMENTS (Notes A, G, and P)		949,261		970,622
ACCRUED INTEREST RECEIVABLE				
Investments	108,216		117,516	
Loans	201,569	309,785	181,423	298,939
RECEIVABLE FROM SWAPS (Notes H and P)				
Borrowings	32,418,962		31,373,104	
Others	9,171,987	41,590,949	6,220,207	37,593,311
OTHER ASSETS				
Property, furniture, and equipment (Note I)	159,865		161,451	
Investment related receivables (Note D)	8,156		2,428	
Swap related collateral (Notes H and P)	2,155,150		1,942,954	
Miscellaneous (Notes N and P)	191,758	2,514,929	159,290	2,266,123

Table A.2: Asian Development Bank Bank Balance sheet, Asset side

A.2 Supervision and Role of Central Banks

Normally, central banks of countries or regulatory authorities are concerned with the financial health of financial institutions operating under their supervision. Therefore, for such organisations having knowledge of all financial institutions, in respect to the kind of operations and how they perform, is crucial because any neglect of such matters may have serious consequences. As such, one may refer to banking panics, banking runs and from a more global perspective; it may spread to other countries e.g. 1992 Asian crises and 2007 global

BALANCE SHEET
AS AT DECEMBER 31, 2012
(UA thousands – Note B)

ASSETS		2012	2011
CASH		881,453	344,156
DEMAND OBLIGATIONS		3,801	3,801
TREASURY INVESTMENTS (Note F)		6,487,512	7,590,469
DERIVATIVE ASSETS (Note G)		1,558,333	1,696,681
NON-NEGOTIABLE INSTRUMENTS			
ON ACCOUNT OF CAPITAL (Note H)		1,974	3,044
ACCOUNTS RECEIVABLE			
Accrued income and charges receivable on loans (Note I)	195,212		193,123
Other accounts receivable	567,456		721,727
		762,668	914,850
DEVELOPMENT FINANCING ACTIVITIES			
Loans, net (Notes D & I)	10,885,804		9,255,493
Hedged loans – Fair value adjustment (Note G)	86,854		49,871
Equity participations (Note J)	438,555		309,762
Other debt securities (Note K)	76,537		79,990
		11,487,750	9,695,116
OTHER ASSETS			
Property, equipment and intangible assets (Note L)	30,421		12,628
Miscellaneous	641		709
		31,062	13,337
TOTAL ASSETS		21,214,553	20,261,454

Table A.3: African Development Bank Balance sheet, Asset side

financial crises. Therefore, it is important to examine how central banks supervise and monitor their banks and financial institutions under their territories. Normally, there are two general methods for central bank to monitor FIs which are called "on site supervision" or examination and "off-site supervision or surveillance".

A.2.1 On-Site Examination

Supervisory authorities generally employ both the on-site examination and off-site surveillance to identify the banks most likely to fail (see(Alton et al., 2000)). It is believed that the most useful tool for discovering the financial condition of banks is on-site supervision or examination. During this method, supervisors/inspectors visit FIs and review the "safeness" and "soundness" of the financial status of banks. However, this method of supervision is time consuming, costly -such as cost of traveling to each FI or in very optimistic way traveling to each bank's head office and internal supervision unit, which is again time consuming and requires much effort in case there are many bank in the country. There is also the risk of corruption. - and cumbersome, since, the supervisory staff have to spent time and effort and intrude into the day-to-day operation of the FI.

A.2.2 Off-site Surveillance and using the CAMELS

On the other hand, during off-site surveillance, the supervisor can be aware of the financial situation, as well as of the on-going picture of the FI employing FIs' financial information. This awareness enables the supervisor to schedule and plan the on-site visits efficiently. Moreover, this method provides banks with incentives to maintain being safe and sound between on-site visits (Yuen and Ling, 2006). Therefore, this method has more advantages compared to the first method, in terms of being less costly, providing more incentive to FIs and creating less corruption. Practically speaking, supervisory authorities can perform due diligence analysis or rate the FIs through linking their systems with the FIs financial systems. In the other words, the objectives of off-site surveillance over the banking system are:

- to monitor the financial situation of individual banks, as well as its situation within the banking system;
- to provide early identification of problems so that corrective actions can be planned in advance;
- to target scarce on-site supervisory resources to areas or activities of greater risk.

There are two types of off-site supervision methods. One is supervisory screen or Micro approach (employing FIs' financial ratios such as CAMEL model) and the other is Econometric methods or Macro approach. The *Micro* approach typically focuses on individual financial statement data of banks, possibly augmented with market price data and is used for forecasting the FI's failure as well. The second approach, which has grown in prominence in recent years, uses macro-economic variables as well as some institutional variables (usually proxied by dummies) to explain and ultimately predict systemic bank crises. These studies typically focus on a large sample of countries, some of which are known to have experienced a banking crisis during a certain period (Bell, 2000).

CAMELS

CAMELS methodology is one of the quantitative methods used for rating FIs and it stands for six categories, namely, Capital, Asset Quality, Management, Efficiency, Liquidity and Sensitivity to market. Some of the ratios in each category are shown in Figure A.1.

Numerous studies have been undertaken in respect to employing CAMELS methodology. As such, one can refer to the research done by Federal Reserve of St. Louis (Gopalan, 2010) where the reasons for bank failures in the 2007 crises were investigated. The study found that the failed banks were particularly exposed to poor asset quality, poor risk management and passive bank management. They examined data on commercial banks that failed between 1990 and 2009 to better understand the financial and supervisory characteristics of failed banks through monitoring the deterioration in banks' CAMELS categories. The threshold of 3 (scale of 1 to 5 of CAMEL, 1 represent for the best and 5 for the worst) was defined as start of deterioration. Moreover, it is worth noting that their review of each failed bank started 14 quarters before its failure. The results of their analysis were not surprising. Banks that had failed experienced deterioration in their asset quality. The deterioration first shows in a bank's earnings level (the "E" component of CAMELS) as banks begin to hold more provision for potential loan losses. This occurs well in advance of other financial health indicators. Moreover, the next CAMELS components to show deterioration were "asset quality" and "management", both hitting the 3 rating, nine quarters before failure. Not surprisingly, the management component rating started to deteriorate soon after the earnings component, reflecting on-going as-

1. EARNINGS PERFORMANCE

(a) Return on assets

(b) Return on equity

(c) Interest spread

(d) Interest margin

(e) Intermediation margin

2. STAFF PRODUCTIVITY

(a) Net income per staff (Rs)

(b) Net income to staff expense

3. LIQUIDITY

(a) Cash ratio

(b) Loans to deposits

4. CAPITAL ADEQUACY

- Capital to risk-adjusted assets
- Earning assets to total assets

5. ASSET QUALITY

- Total Provisions to Loans Outstanding
- Annual Provision to Loans Outstanding

Figure A.1: Financial performance ratios
Slevavinayagam (1995)

set quality issues and regulatory initiatives by bank supervisors to clearly communicate with management. The "capital" component of the CAMELS rating was the next one, which hit the first warning level, seven quarters before failure. The literature suggests that capital ratios often do not fall as quickly as asset quality deterioration because of the ability of banks, in some cases, to raise new capital. Other institutions attempt to increase capital ratios by reducing the size of the balance sheet, shedding assets through reduced lending or asset sales. The final two CAMELS ratings to fall are "liquidity" (six quarters out) and "sensitivity to risk" (two quarters out).

Financial Stability (soundness) Indicators (FSIs)

As stated by Clair Clair (2004) most of the central banks rely on qualitative analysis, which is based on the Financial Stability Indicators. Although these indicators are useful for the diagnosing of the health of financial institutions, it is unable to capture and fully define the relation between the macro-economic factors and their impacts on financial soundness of FIs, especially during early stages. Therefore, the requirement for a quantitative macro-micro model has become more vital. In this regard, some work is under process by the International Monetary Fund (IMF). The organisation is launching a project on financial soundness indicators. Notwithstanding the need for internationally comparable set of financial sector indicators, it might not be enough for detecting the early warning signals of financial sector problems. The diversity regarding financial sector development or other particularities make the universal set of indicators inefficient for each individual country. Likewise, the threshold levels signalling crisis would have large deviations for mature and emerging markets.

Therefore, IMF has encouraged national authorities to work on early warning system aligned to the country context. As the field undergoes rapid development, approaches that are more complex are gradually complementing the framework such as sophisticated econometric and risk models.

Econometrics models

Apart from the CAMELS methodology, another types of methodologies exists for detecting the fragility of the FIs before it happens which are econometrics methods. It can now be claimed that, using only the micro (financial) data of the financial institution - such as the work done by the central bank of St. Louis and some other similar works, may not provide an accurate picture. Generally, in econometric approach, several FI financial ratios are employed which can be expected to have major impacts on financial markets. As such, one can refer to liquidity, leverage and efficiency ratios and macro-economic ratios including but not limited to inflation rate, interest rate and GDP growth.

As another research in this field includes a study of the Central Bank of Singapore (Clair, 2004) which used 9 single econometrics models employing non-performing loans ratio as their dependent variable and the index for banks' fragility and macro and micro variables as their descriptive variables. In their research, micro data of 3 commercial banks has been used in a short term period of one year[1] Their model is shown in Figure A.2, Figure A.3 and Figure A.4.

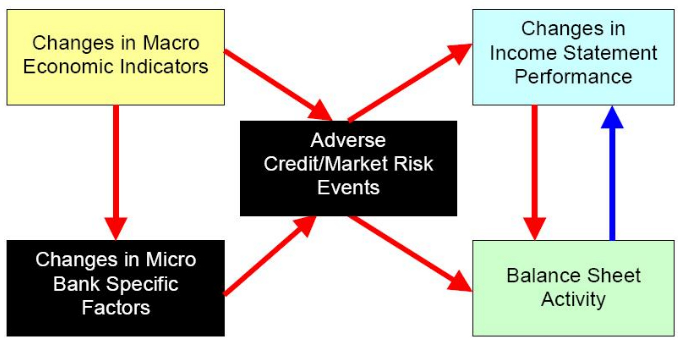


Figure A.2: An ideal framework of determinant of Bank performance and resilience

Clair (2004)

The study found that some macro-economic factor such as interest rates, exchange rates, unemployment, aggregate demand have the most significant impact from the 29 macro variables on the financial statements of the three banks and the employed banks micro level variables are income, expenditure, profitability, labour demand, capital holdings and liquidity. Moreover, they have shown a relation between business cycle and financial resilience. Additionally, several variables as financial stability or resilience like as NPL to total as-

[1]criticism of their work might include employing a short period of time, using a limited number of FIs, as well as employing single equation models which can fail to capture the joint-determination of changes in financial statement and how these are influenced by changes in macro environment.

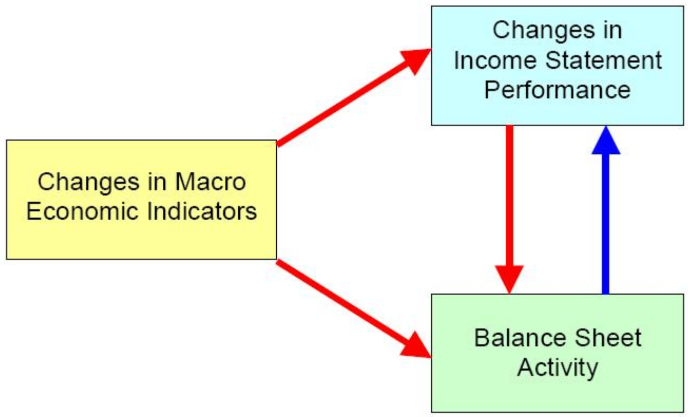


Figure A.3: A feasible framework of determinant of Bank performance and resilience
Clair (2004)

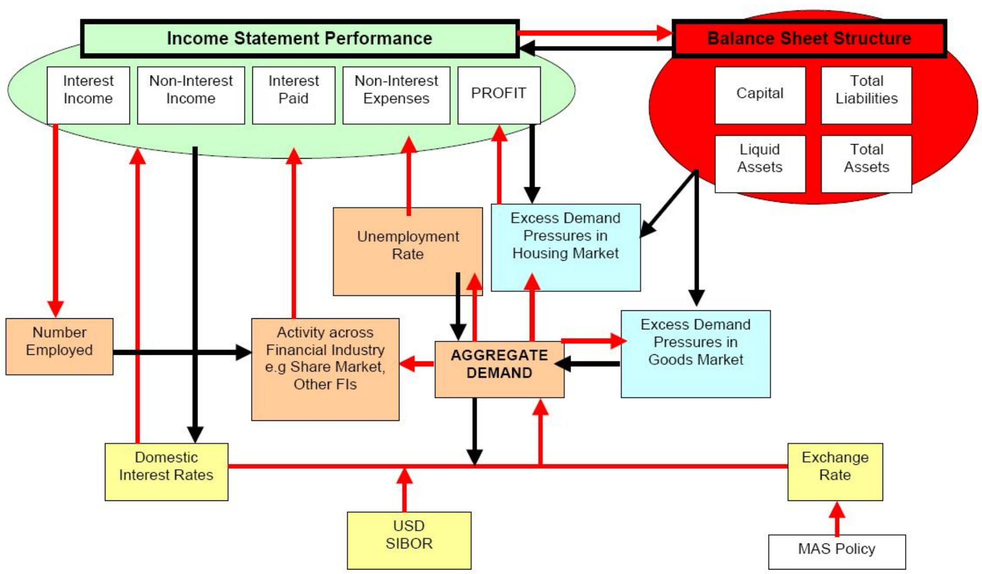


Figure A.4: Inter linkage between macro environment and banking
Clair (2004)

sets, changes in total capital and changes in total liquidity have been employed. The results claimed that the bank specific factors define the likelihood of bank failure while the macro-environment factors determine the financial performance more generally and timing of bank failures.

The other important issue in developing quantitative modelling for banks and financial institutions is that one must define the boundary for the analysis, for example, some of the financial institutions operate globally, therefore one must define whether or not one would like to consider the FI parent company operating in single country or the entire group operating in multiple countries. Pesola (2007) in another study conducted by for bank of Finland showed that the more fragile a banking system is, the more likely it is to experience problems when an unexpected shock hits. The study has used a macro-economic model with the dependent variable of net loan losses to lending using a panel data set between 1980 and 2004. The empirical model developed builds on the following three novelties: 1) a banking sector panel of loan loss data from ten European countries, 2) joint effect of aggregate indebtedness and macro-economic shocks on loan losses and 3) use of macro-economic forecasts for expectations in surprise variables. A surprise (an unexpected shock) is the difference between realised and expected outcome. The annual aggregate banking sector loan loss data was provided for this study by the central banks of Belgium, Denmark, Finland, Germany, Greece, Iceland, Norway, Spain, Sweden and the United Kingdom. In the period under their review, a relatively large number of banking crises had occurred in several of these countries, notably in Scandinavia. A central idea to be tested in their model was that financial fragility, measured by aggregate indebtedness, affects loan losses of banks jointly with macro-economic shocks.

Banks' loan losses = f(macroeconomic shock * financial fragility)

The study concluded that the effect of a macro-economic shock on loan losses is non-linear: the effect of a shock is amplified if the prevailing fragility (indebtedness) is high. The researchers employed macro-economic shock variables (from the IMF's macro prudential indicators) such as economic growth, balance of payments, inflation, interest and exchange rates, lending and asset price booms etc. The research concluded that high customer indebtedness combined with adverse macroeconomic surprise shocks to real interest rates contributed to increase in loan losses and distress in the banking sector.

In this regard, the econometric models are more efficient to trace such effects. As the relation between macro-economic factors are overly complicated, without considering macroeconomic factors, studies may only go one step forward to trace these relations and try to predict the financial fragility of the banks and financial instability, to set proper risk based pricing, proper loss provisioning and in some cases inform the credit bureau to cancel the relationship with the fragile bank. Therefore, one can agree with (Clair, 2004) stating that one can be sure that the quantitative analysis are always more important and accurate than the qualitative analysis. Furthermore, the International Monetary Fund also emphasised and encouraged to develop quantitative solutions for detecting the effects of macro-environment on the financial sector.

A.3 Methods of investigation

Reflecting from various perspectives from which the subject matter is studied, the analysis in this study makes use of both empirical and theoretical methods. The methodological approach in this dissertation is based on data mining technique, which is defined as discovering new and informative knowledge, such as patterns, associations, rules, changes, anomalies and significant structure from large amounts of data stored in data banks and other information repositories. This process is currently called as a Knowledge Discovery in Databases (KDD) (Valickov and Solomatine, 2000). This process generally consists of an iterative sequence of the following steps:

1. data selection, where data relevant to the analysis, is retrieved from database;
2. data cleaning which handles noisy, missing or irrelevant data;
3. data integration (enrichment), where multiple heterogeneous data may be integrated into one;
4. data transformation (coding), where data is transformed or consolidated into forms appropriate for different mining algorithms;
5. data mining, which is an essential process where intelligent methods are applied in order to extract hidden and valuable knowledge from data;
6. knowledge representation, where visualisation and knowledge representation techniques are used to present the mined knowledge to the user (Valickov and Solomatine, 2000).

A large set of data analysis methods have been developed in statistics over numerous years of studies. Machine learning and statistical learning theory have contributed significantly to classification and induction problems. Neural networks have shown their effectiveness in classification, prediction and clustering analysis tasks. One can state that one specific technique, which characterises data mining, does not exist. Any technique that helps to extract more out of the data sets in an autonomous and intelligent way may be classified as a data mining technique.

In general, data mining tasks can be classified into two categories of: **description**[2] and **prediction**[3]. The distinction between description and prediction is not very clear. Predictive models can also be descriptive (to the degree that they are understandable), and descriptive models can be used for prediction. To achieve these goals, the categories of prediction, as well as description, are associated with five basic operations, as presented in Figure A.5.

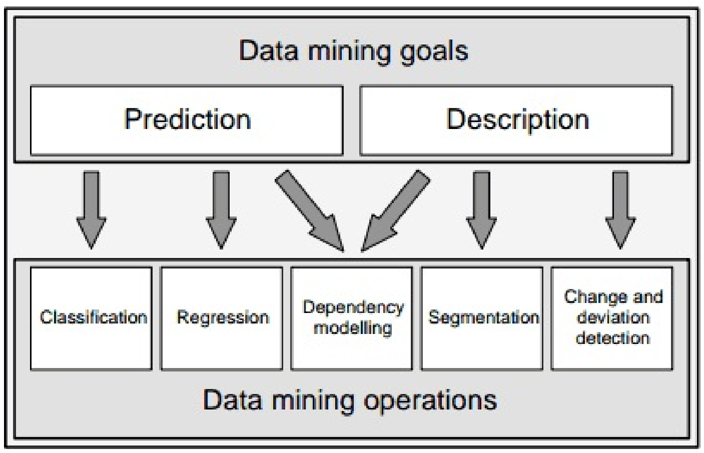


Figure A.5: The connection between data mining goals and operations (Valickov and Solomatine, 2000)

WWhile there are only few basic data mining operations, there are wide varieties of data mining techniques which make these operations possible. Normally, data mining systems do not include each of these techniques, but they often combine two or more different techniques between which the user/engineer can choose - depending on the specific problem. Therefore, potential users should survey the most

[2]Finding human interpretable patterns, associations or correlations describing the data.

[3]Constructing one or more sets of data models (rule set, decision tree and neural nets), performing inference on the available set of data and attempting to predict the behavior of new data sets.

common techniques, in order to decide which one will suit their engineering needs better. Figure A.6 presents some common techniques assigned to basic data mining operations, emphasising classification and regression techniques.

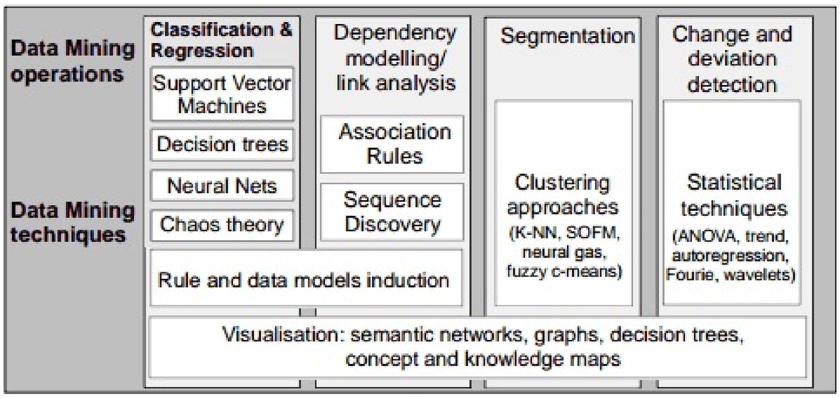


Figure A.6: Data mining operations and techniques (Valickov and Solomatine, 2000)

In literature, forecasting models are categorised in three main groups: statistical methods, theoretical methods and models using soft-computing techniques (see Figure A.7). According to literature, 64% of studies use statistical methods, 25% use soft-computing techniques and the remaining use other types of models (Korol, 2012).

Prerequisites for employing statistical models for credit risk forecasting are:

1. Indicators needs to have normal distributions,

2. Indicators must be independent,

3. Indicators must have a high discriminative ability of separating solvent entities from insolvent ones,

4. Observations for each individual object (solvent and insolvent companies/clients) must be complete - i.e. should have values for all indicators of all entities,

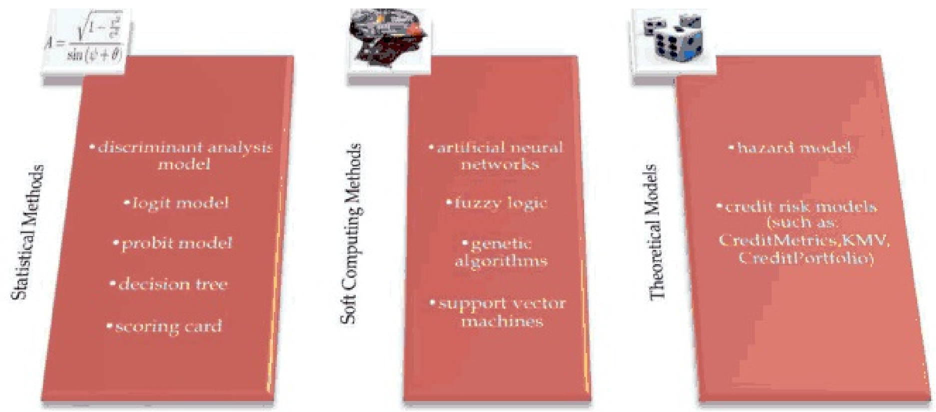


Figure A.7: Classification of forecasting models
(Korol, 2012)

5. Object classifications must be clearly defined - belonging to one group excludes its belonging to a second group.

Statistical and artificial neural network models are a good option for scoring/rating purposes when there is sufficient amount of defaulted customer's data. Other theoretical models such as KMV models for defining the bankrupt customers is also applicable when the market value of the customers is known (a company is considered as being bankrupt when market value of its assets falls below net worth of liabilities).

However, in contrast to the above-mentioned models, in the absence of customers default story, a combination of data mining techniques with fuzzy models can cope with imprecisely defined problems, incomplete data, impression and uncertainty. The process of business failure is affected by many internal and external factors, which its prediction is imprecise and ambiguous. However, with help of fuzzy concept one can cope with this problem (Korol, 2012). Moreover, in literature, numerous researchers have suggested that the learning database for statistical models should be composed of a balanced sample (consisting of 50% bankrupt and 50% non-bankrupt cases). This enables the model to distinguish between "bad" and "good". However, in reality, there are a small number of bankrupt entities than compared to non-bankrupt ones.

The other drawbacks of such statistical models e.g. Logit, Probit and discriminant analysis is the possibility of manipulation of the threshold in order to maximise the classification results of these models (Nwogugu, 2007). Comparing the fuzzy logic method with other soft-computing techniques such as neural network, one may refer to the inability to justify the result of such models as they perform with black box systems. For instance, analysis of the process for assigning individual variables weights is complex and difficult to interpret. These models do not provide course of reasoning, leading to certain assessments. They simply provide their outcome, without being able to trace further evidence, leading to a final conclusion.

Appendix B

Appendix Chapter 3

B.1 Result for 32 European Countries data set

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ROA(-1)	0.600884	0.297624	2.02	0.043	0.0175517	1.184216
Cost of Employee/Operating Revenue	-0.00658	0.022429	-0.29	0.769	-0.0505366	0.037385
GDP Growth (Annula %)	0.134366	0.035461	3.79	0	0.0648645	0.2038682
Inflation, GDP deflator (Annual %)	-0.05478	0.052257	-1.05	0.295	-0.1571995	0.0476428
Credit Period	0.008889	0.0046	1.93	0.053	-0.0001271	0.0179048
Share of trade in GDP (in per cent)	0.032691	0.021772	1.5	0.133	-0.0099816	0.0753626
Asset share of state-owned banks (in per cent)	-0.10448	0.039302	-2.66	0.008	-.1815088 -	0.0274484
Sales/Net Working Capital	0.004191	0.001545	2.71	0.007	0.0011626	0.0072201
EBRD index of banking sector reform	3.616936	2.145808	1.69	0.092	-0.5887692	7.822642
Stock market capitalisation (in per cent of GDP)	0.030407	0.011799	2.58	0.01	0.0072805	0.0535326
Budgetary subsidies and current transfers (in per cent of GDP)	0.000175	0.000258	0.68	0.496	-0.0003292	0.00068
Constant	-3.28027	2.241566	-1.46	0.143	-7.673659	1.113117
Number of instruments = 26						

Wald test		
chi2(9)	=1760.61	
Prob > chi2	= 0.0000	
Arellano-Bond test for zero autocorrelation in first-differenced errors		
Order	**z**	**Prob>z**
1	-4.9482	0
2	-1.6566	0.0976
H0:no autocorrelation		
Sargan test for overidentifying restrictions		
chi2(20)	5.610112	
Prob > chi2	0.9754	
H0: overidentifying restrictions are valid		

Table B.1: ROA determinants for 32 European countries; employing General Method of Moment

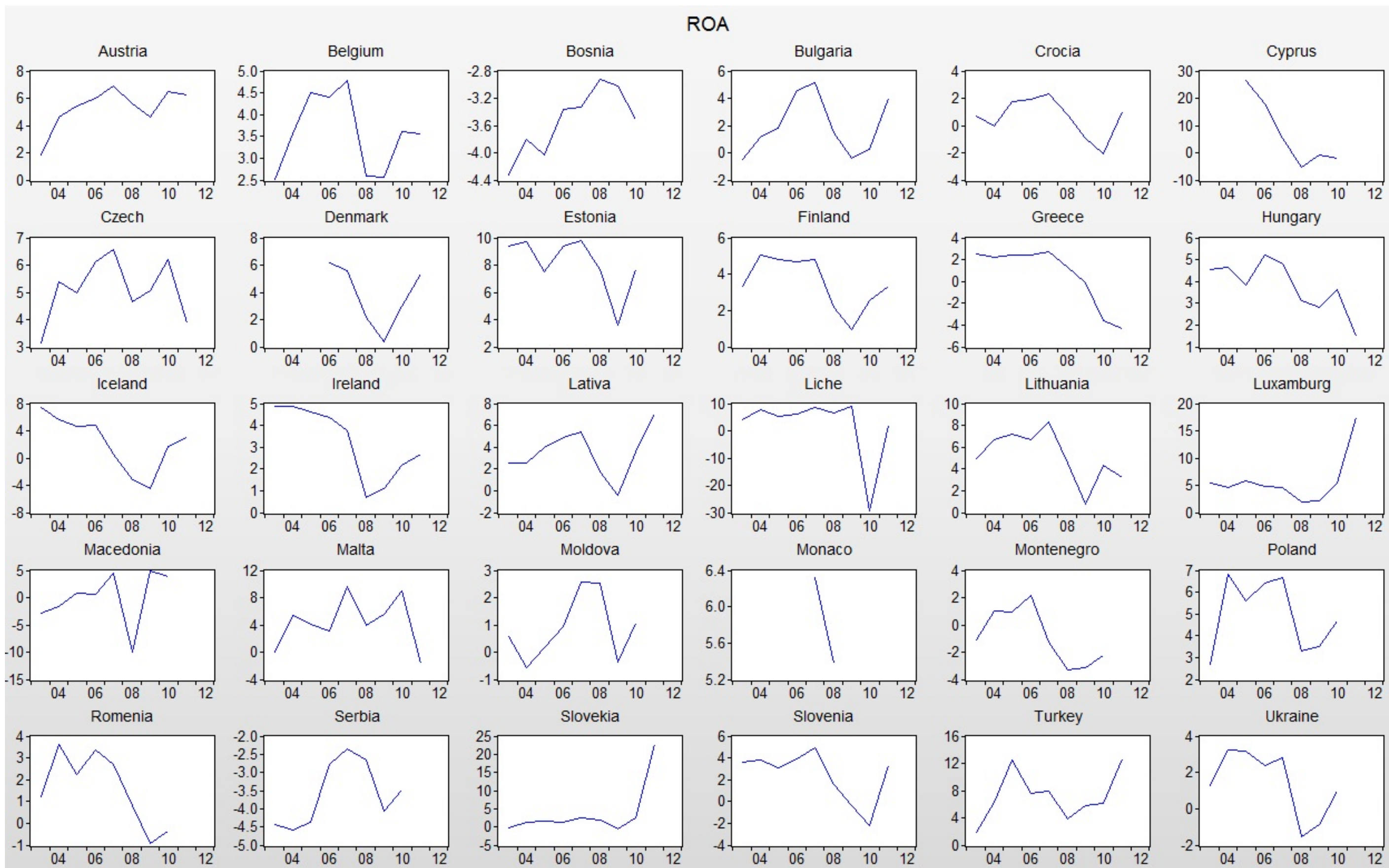


Figure B.1: ROA trend for 32 European countries

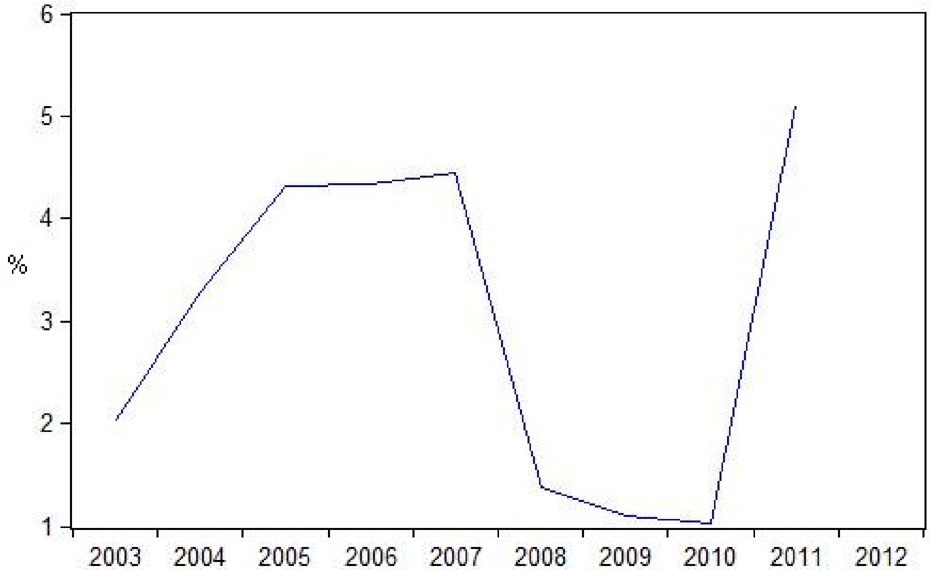


Figure B.2: ROA trend for 32 European countries (average)

Appendix **C**

Appendix Chapter 4

C.1 Types of membership functions

S-shape membership function defines as:

$$\mu_s(x,a,b,c) = \begin{cases} 0, & for\ x \leq a \\ 2[(x-a)/(c-a)]^2, & for\ a \leq x \leq b \\ 1-2[(x-a)/(c-a)]^2, & for\ b \leq x \leq c \\ 1, & for\ x \geq c \end{cases}$$

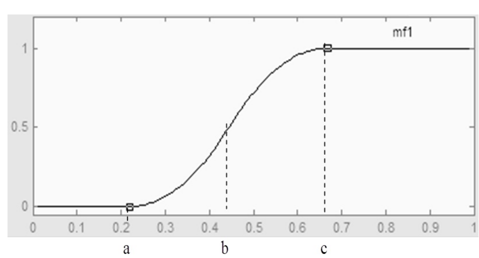


Figure C.1: S-Shape membership function

Z-shaped represents an asymmetrical polynomial curve open to the left and is defined as following:

$$\mu_Z(x,a,b,c) = \begin{cases} 1, & for\ x \leq a \\ 1 - 2[(x-a)/(c-a)]^2, & for\ a \leq x \leq b \\ 2[(x-a)/(c-a)]^2, & for\ b \leq x \leq c \\ 0, & for\ c \geq x \end{cases}$$

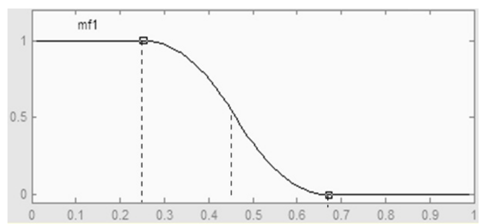


Figure C.2: Z-Shape membership function

Triangular MFs specifies by three parameters a, b, c as follows:

$$triangle(x;a,b,c) = \begin{cases} 0, & for\ x \leq a \\ \frac{x-a}{b-a}, & for\ a \leq x \leq b \\ \frac{c-x}{c-b}, & for\ b \leq x \leq c \\ 0, & for\ c \geq x \end{cases}$$

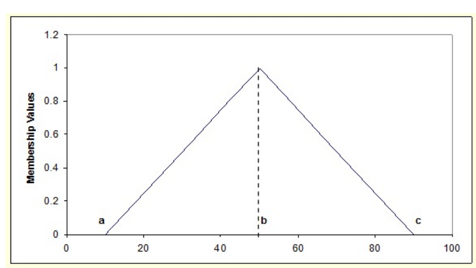


Figure C.3: Triangular membership function

Trapezoidal MFs is specifies by four parameters a, b, c, d as following:

$$trapezoid(x,a,b,c) = \begin{cases} 0, & for\ x \leq a \\ \frac{x-a}{b-a}, & for\ a \leq x \leq b \\ 1, & for\ b \leq x \leq c \\ \frac{d-x}{d-c}, & for\ c \leq x \leq d \\ 0, & for\ d \geq x \end{cases}$$

An alternative concise expression using min and max is:

$$trapezoid(x;a,b,c,d) = max(min(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}), 0) \tag{C.1}$$

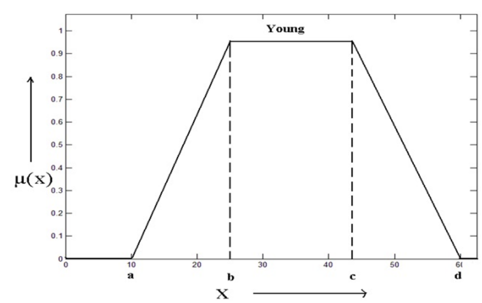


Figure C.4: Trapezoidal membership function

Gaussian membership function is specified by two parameters a, b as following:

$$\mu(x,a,b) = e^{\frac{-(x-b)^2}{2a^2}} \tag{C.2}$$

The graph given in Figure C.5 is for parameters a = 0.22, b = 0.78

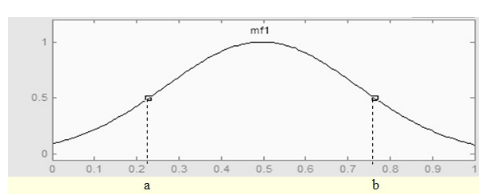


Figure C.5: Gaussian membership function

Pi Function Pi-shaped curve is a spline-based curve which is named so because of its shape. This membership function is evaluated at four points namely a, b, c, and d. The parameters a and d locate the feet of the curve, while b and c locate its shoulders. In the graph given in Fig. 10.14, a = 2, b = 4, c = 5, and d = 9.

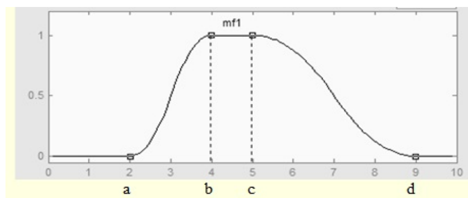


Figure C.6: Pi membership function

Vicinity function To represent the statement x is close to x_0, where x_0 is any fixed value of x, vicinity function using S function as following can be used:

$$\mu_V(x,b,a) = \begin{cases} S(x, a-b, x-b/2, a), & for\ x \leq a \\ 1 - S(x, a, x+b/2, a+b, & for\ x \geq a \\ 0, & for\ d \geq x \end{cases}$$

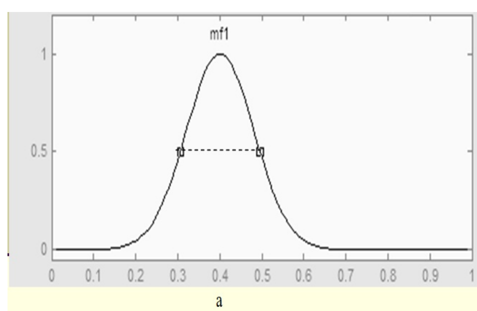


Figure C.7: Vicinity membership function

C.2 Fuzzy Methods

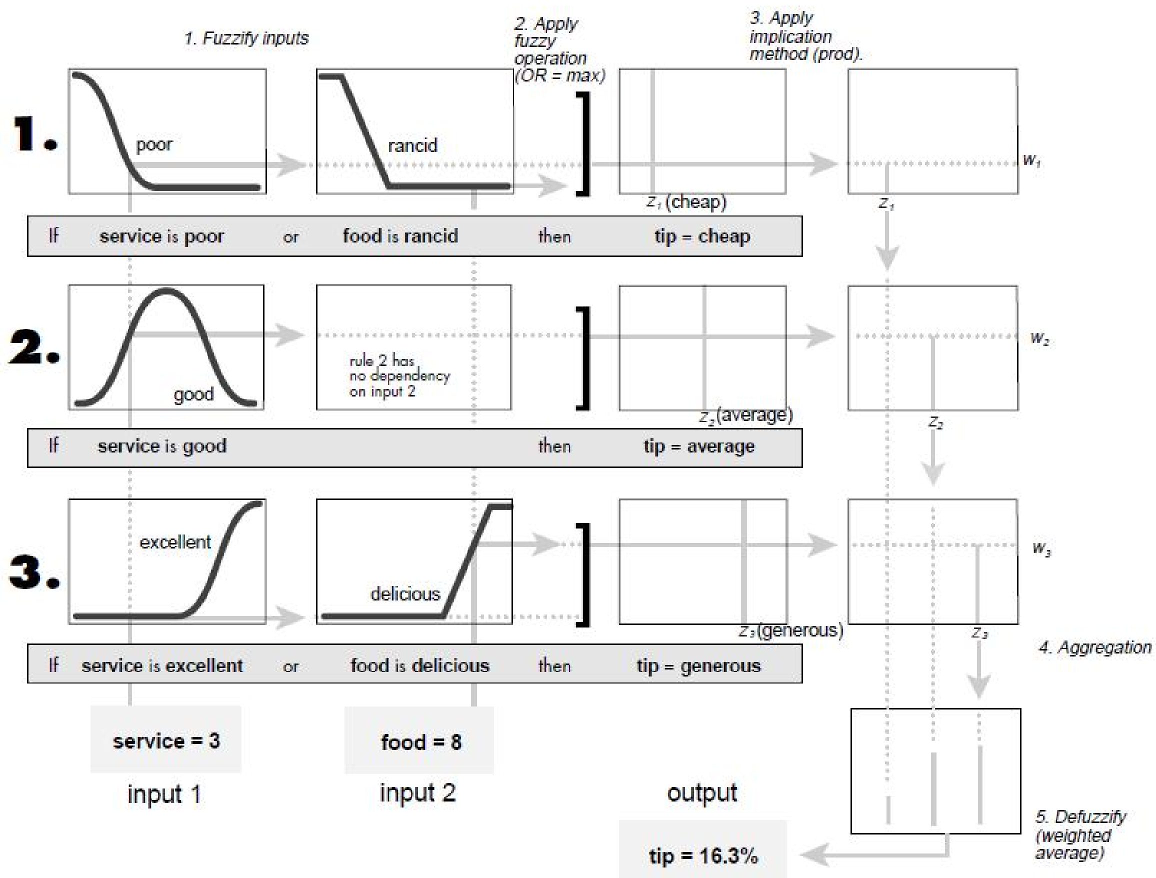


Table C.1: Two Input Sugeno-Takagi Model

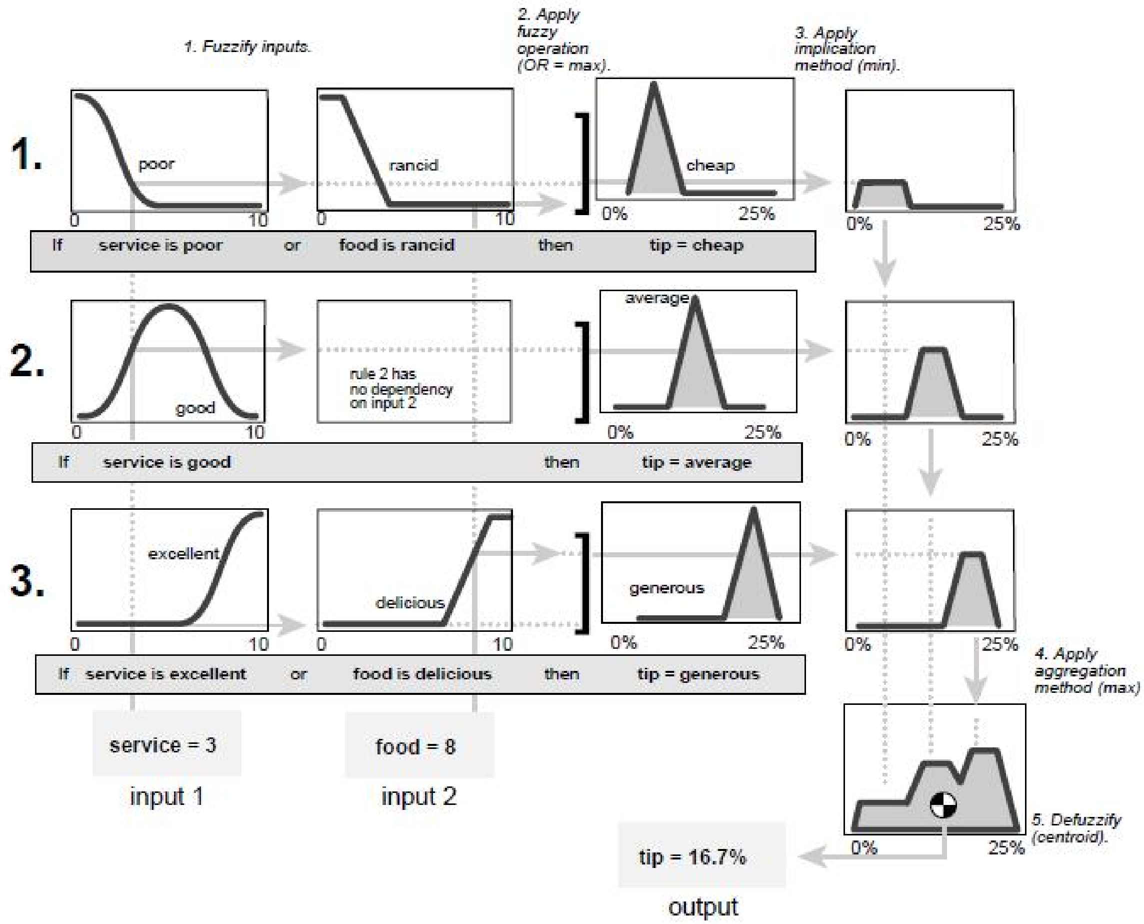


Table C.2: Two Input Mamdani Model

C.3 FuzzyTech documentations

C.3.1 Financial Institution's Scoring Model

1 General Information

Author:	
Created:	Friday, February 08, 2013
Print Date:	Sunday, March 30, 2014

Edition

Edition Name:	fuzzyTECH 5.54d Professional Edition
Neuro Modul:	NeuroFuzzy add-on Module installed

.1 Table of Contents

.2 List of Figures

.3 List of Tables

.4 List of Abbreviations

Compute MBF	Compute Membership Function (Fuzzification Method)
Hyper CoM	Hyper Center of Maximum (Defuzzification Methode)
BSUM	Bounded Sum Fuzzy Operator for Result Aggregation
MIN	Fuzzy Operator for AND Aggregation
MAX	Fuzzy Operator for OR Aggregation
GAMMA	Compensatory Operator for Aggregation
PROD	Fuzzy Operator for Composition
LV	Linguistic Variable
MBF	Membership Function
RB	Rule Block

2 chapter4model-underwork-2

.1 Project Description

Input Variables	10
Output Variables	1
Intermediate Variables	8
Rule Blocks	3
Rules	684
Membership Functions	62

Table 1: Project Statistics

.2 System Structure

The system structure identifies the fuzzy logic inference flow from the input variables to the output variables. The fuzzification in the input interfaces translates analog inputs into fuzzy values. The fuzzy inference takes place in rule blocks which contain the linguistic control rules. The output of these rule blocks are linguistic variables. The defuzzification in the output interfaces translates them into analog variables.

The following figure shows the whole structure of this fuzzy system including input interfaces, rule blocks and output interfaces. The connecting lines symbolize the data flow.

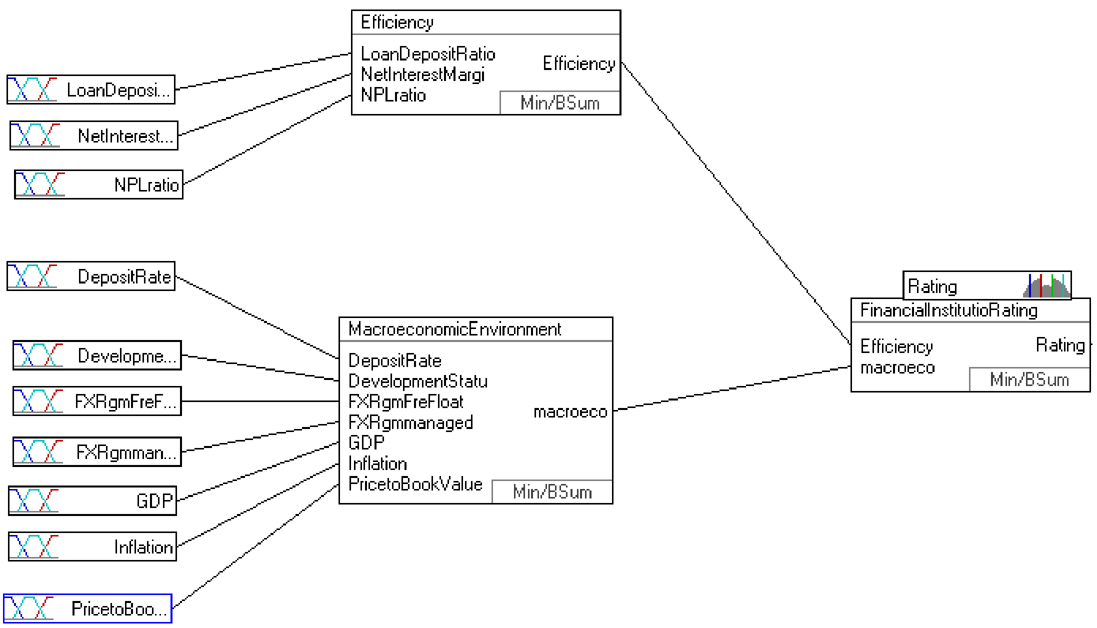
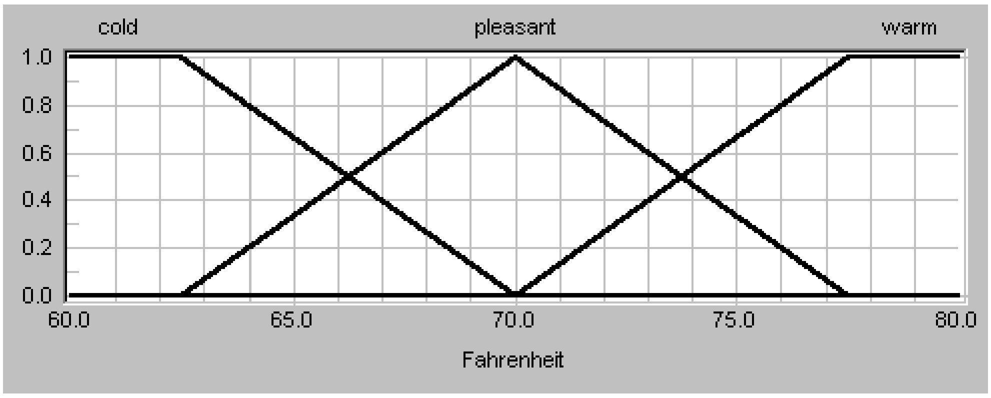


Figure 1: Structure of the Fuzzy Logic System

.3 Variables

This chapter contains the definition of all linguistic variables and of all membership functions.
Linguistic variables are used to translate real values into linguistic values. The possible values of a linguistic variable are not numbers but so called 'linguistic terms'.

For example:
To translate the real variable 'temperature' into a linguistic variable three terms, 'cold', 'pleasant' and 'warm' are defined. Depending on the current temperature level each of these terms describes the 'temperature' more or less well. Each term is defined by a membership function (MBF). Each membership function defines for any value of the input variable the associated degree of membership of the linguistic term. The membership functions of all terms of one linguistic variable are normally displayed in one graph. The following figure plots the membership functions of the three terms for the example 'temperature'.



Membership Function of 'temperature'

A 'temperature' of 66 °F is a member of the MBFs for the terms:

cold	to the degree of 0.8
pleasant	to the degree of 0.2
warm	to the degree of 0.0

Linguistic variables have to be defined for all input, output and intermediate variables. The membership functions are defined using a few definition points only.

The following tables list all variables of the system as well as the respective fuzzification or defuzzification method. Also the properties of all base variables and the term names are listed.

.1 Inputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	DepositRate		Units	2	14	3	low term1 high
2	DevelopmentSta tu		Units	0	1	0	Developing Developed
3	FXRgmFreFloat		Units	0	1	0	low high
4	FXRgmmanage d		Units	0	1	0	freeFloat Managned
5	GDP		Units	3	11	3	term2 term3 term4
6	Inflation		Units	79	134	79	term2 term3 term4
7	LoanDepositRati o		Units	-2	1000	0	term2 term3 term4
8	NetInterestMargi		Units	-2.36	360	0	low medium high
9	NPLratio		Units	0	50	0.5	term2 term3 term4
10	PricetoBookValu e		Units	0	7	0	low medium high

Table 2: Variables of Group "Inputs"

Fuzzification Methods

Compute MBF

Categorical Variable

Fuzzy Input

Look up MBF

Display

.2 Outputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
11	Rating		Units	0	100	0	term1 term2 term3 term4 term5 term6 term7 term8 term9 term10 term11

Table 3: Variables of Group "Outputs"

Defuzzification Methods

Center of Maximum (CoM)	Mean of Maximum (MoM)
Center of Area (CoA)	Hyper CoM
Fuzzy Output	Force

The default value of an output variable is used if no rule is firing for this variable.Different methods can be used for the defuzzification, resulting either into the 'most plausible result' or the 'best compromise'.

The 'best compromise' is produced by the methods:
CoM (Center of Maximum)
CoA (Center of Area)
CoA BSUM, a version especially for efficient VLSI implementations

The 'most plausible result is produced by the methods:
MoM (Mean of Maximum)
MoM BSUM, a version especially for efficient VLSI implementations

.3 Intermediates

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
12	country		-	-	-	-	low medium high
13	Efficiency		-	-	-	-	low medium high
14	firmspecific		-	-	-	-	low medium high
15	macroeco		-	-	-	-	low medium high
16	Management		-	-	-	-	low medium high
17	Privitization1		-	-	-	-	low medium high
18	sponsor		-	-	-	-	low medium high
19	Sponsor		-	-	-	-	low medium high

Table 4: Variables of Group "Intermediates"

.4 Input Variable "DepositRate"

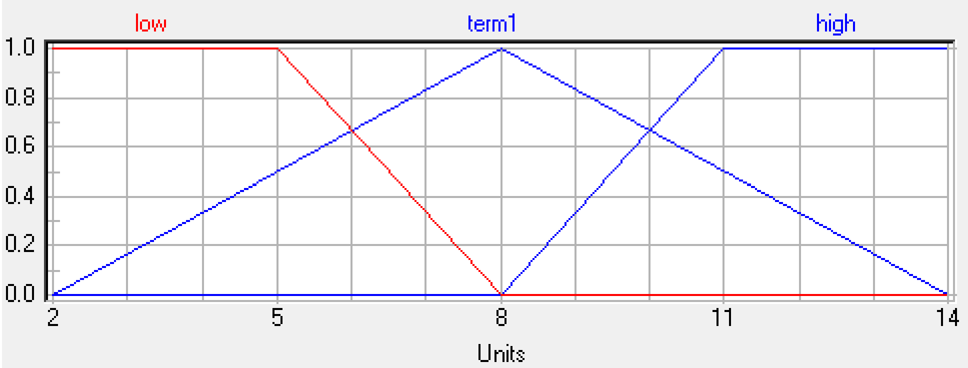


Figure 2: MBF of "DepositRate"

Term Name	Shape/Par.	Definition Points (x, y)		
low	linear	(2, 1) (14, 0)	(4.9998, 1)	(8, 0)
term1	linear	(2, 0)	(8, 1)	(14, 0)
high	linear	(2, 0) (14, 1)	(8, 0)	(11, 1)

Table 5: Definition Points of MBF "DepositRate"

.5 Input Variable "DevelopmentStatu"

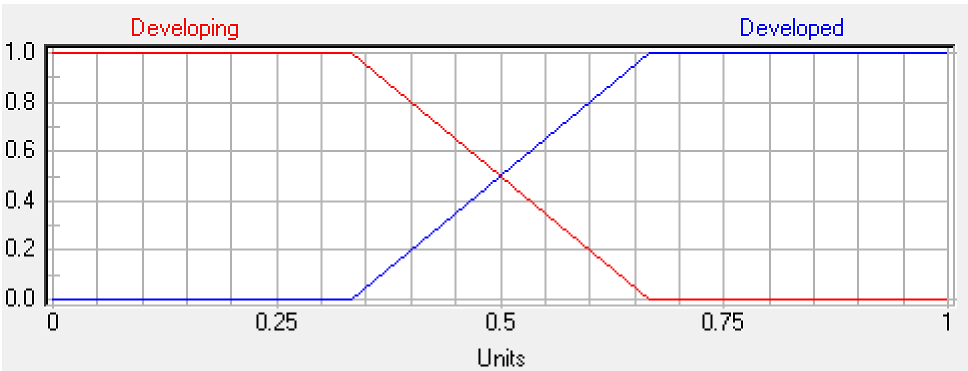


Figure 3: MBF of "DevelopmentStatu"

Term Name	Shape/Par.	Definition Points (x, y)		
Developing	linear	(0, 1) (1, 0)	(0.33336, 1)	(0.66664, 0)
Developed	linear	(0, 0) (1, 1)	(0.33336, 0)	(0.66664, 1)

Table 6: Definition Points of MBF "DevelopmentStatu"

.6 Input Variable "FXRgmFreFloat"

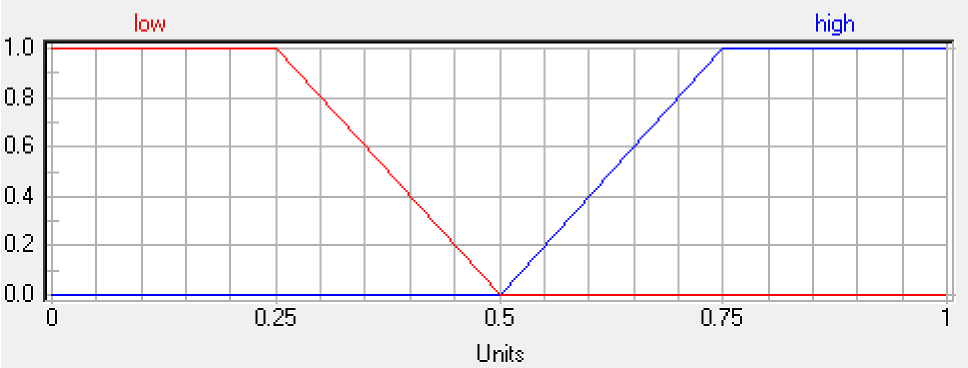


Figure 4: MBF of "FXRgmFreFloat"

Term Name	Shape/Par.	Definition Points (x, y)		
low	linear	(0, 1) (1, 0)	(0.24998, 1)	(0.5, 0)
high	linear	(0, 0) (1, 1)	(0.5, 0)	(0.75, 1)

Table 7: Definition Points of MBF "FXRgmFreFloat"

.7 Input Variable "FXRgmmanaged"

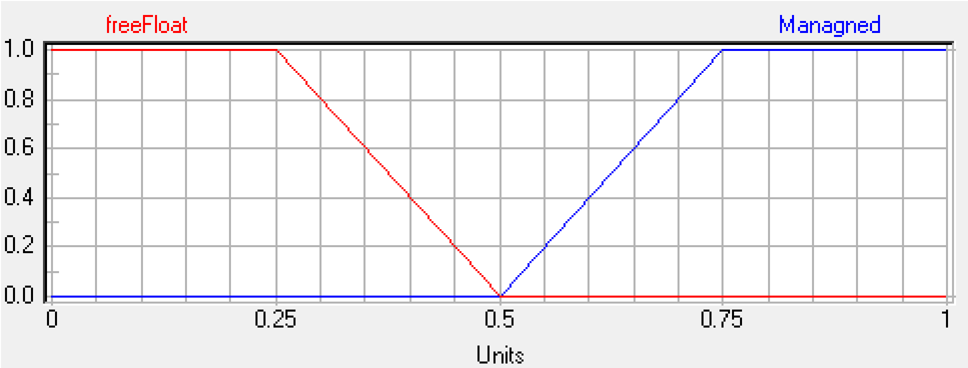


Figure 5: MBF of "FXRgmmanaged"

Term Name	Shape/Par.	Definition Points (x, y)		
freeFloat	linear	(0, 1) (1, 0)	(0.25, 1)	(0.5, 0)
Managned	linear	(0, 0) (1, 1)	(0.5, 0)	(0.75, 1)

Table 8: Definition Points of MBF "FXRgmmanaged"

.8 Input Variable "GDP"

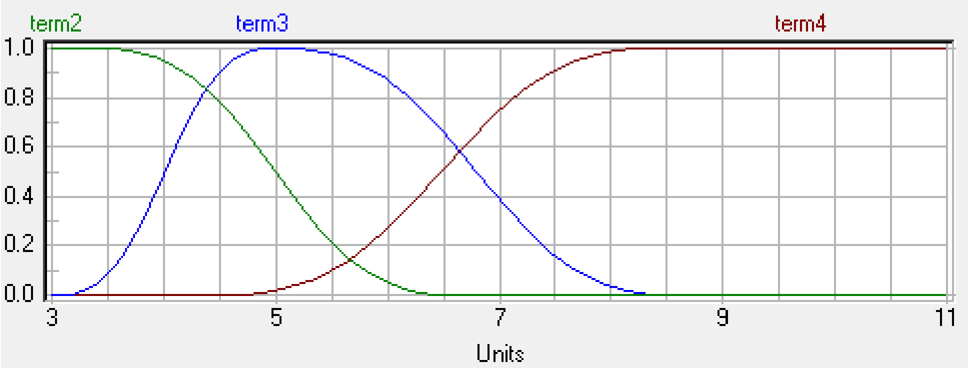


Figure 6: MBF of "GDP"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(3, 1) (11, 0)	(3.376, 1)	(6.624, 0)
term3	S-Shape/0.50	(3, 0) (8.606875, 0)	(3.03425, 0) (11, 0)	(4.982875, 1)
term4	S-Shape/0.50	(3, 0) (11, 1)	(4.50425, 0)	(8.43575, 1)

Table 9: Definition Points of MBF "GDP"

.9 Input Variable "Inflation"

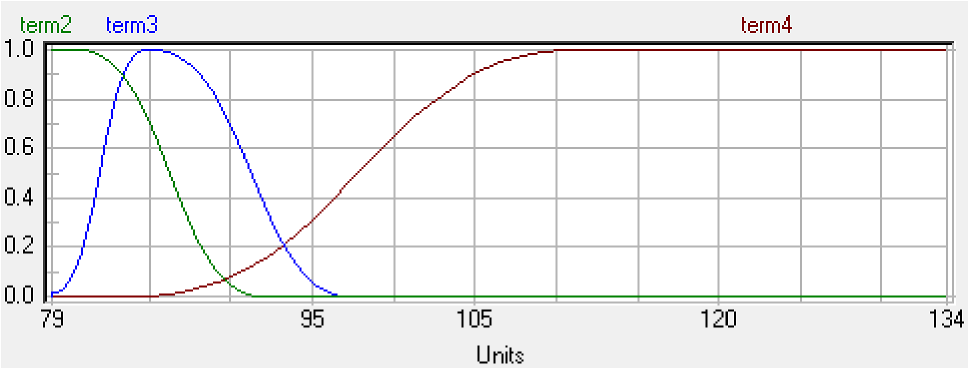


Figure 7: MBF of "Inflation"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(79, 1) (134, 0)	(80.411, 1)	(92.162, 0)
term3	S-Shape/0.50	(79, 0) (97.569, 0)	(79, 0.01828) (134, 0)	(84.875, 1)
term4	S-Shape/0.50	(79, 0) (134, 1)	(83.4, 0.00182)	(112.141, 1)

Table 10: Definition Points of MBF "Inflation"

.10 Input Variable "LoanDepositRatio"

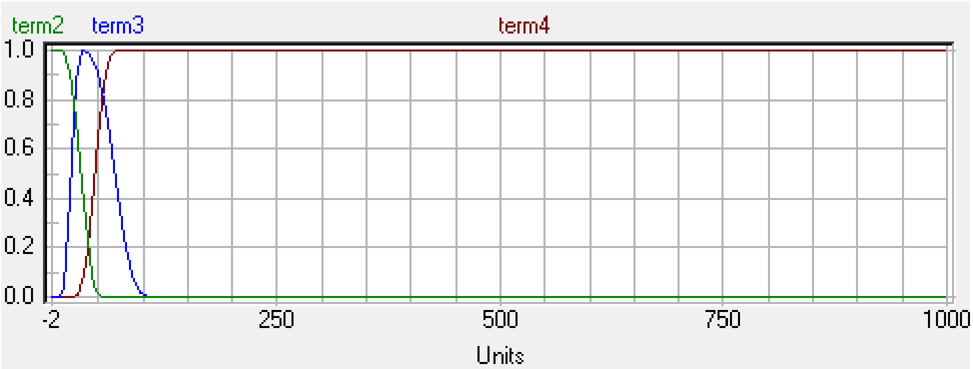


Figure 8: MBF of "LoanDepositRatio"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(-2, 1) (1000, 0)	(6.58, 1)	(53.66, 0)
term3	S-Shape/0.50	(-2, 0) (105.06, 0)	(6.58, 0) (1000, 0)	(32.24, 1)
term4	S-Shape/0.50	(-2, 0) (1000, 1)	(23.66, 0)	(70.8, 1)

Table 11: Definition Points of MBF "LoanDepositRatio"

.11 Input Variable "NetInterestMargi"

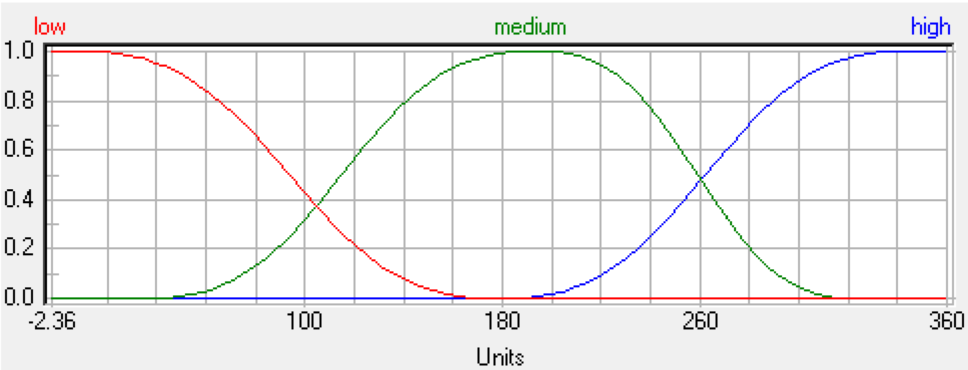


Figure 9: MBF of "NetInterestMargi"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(-2.36, 1) (360, 0)	(8.4700000000001, 1)	(178.82, 0)
medium	S-Shape/0.50	(-2.36, 0) (323.76, 0)	(34.81, 0) (360, 0)	(194.3, 1)
high	S-Shape/0.50	(-2.36, 0) (360, 1)	(178.82, 0)	(344.52, 1)

Table 12: Definition Points of MBF "NetInterestMargi"

.12 Input Variable "NPLratio"

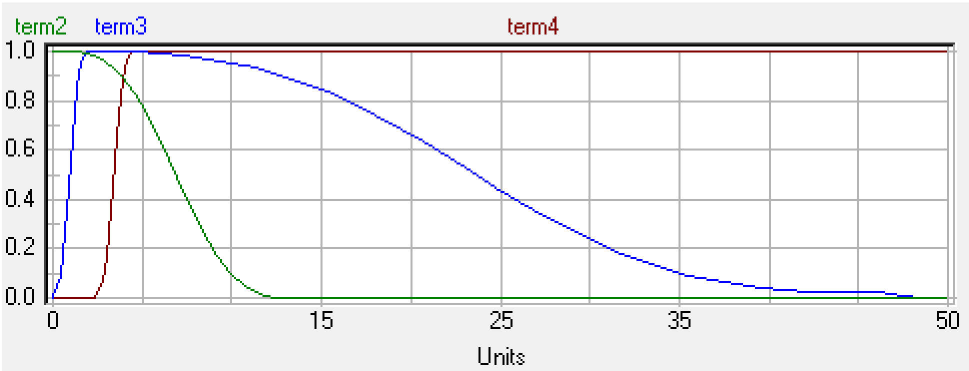


Figure 10: MBF of "NPLratio"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(0, 1) (50, 0)	(0.64099999999999, 1)	(13.034, 0)
term3	S-Shape/0.50	(0, 0) (44.874, 0.02804)	(0, 0.00934) (50, 0)	(1.923, 1)
term4	S-Shape/0.50	(0, 0) (50, 1)	(2.351, 0)	(4.486, 1)

Table 13: Definition Points of MBF "NPLratio"

.13 Input Variable "PricetoBookValue"

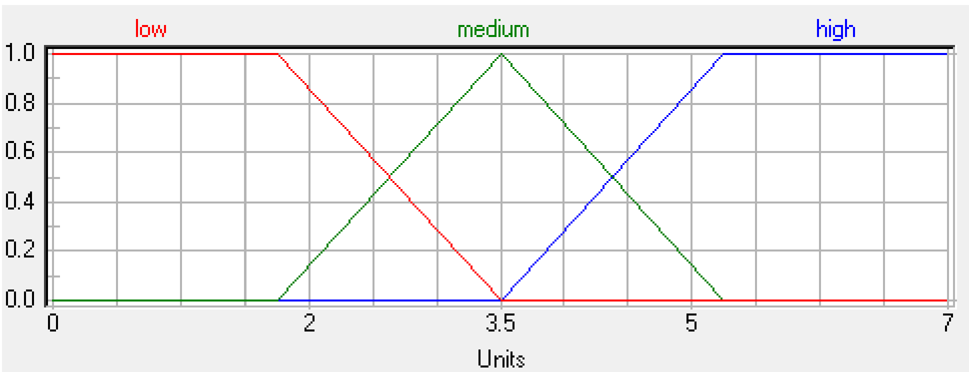


Figure 11: MBF of "PricetoBookValue"

Term Name	Shape/Par.	Definition Points (x, y)		
low	linear	(0, 1) (7, 0)	(1.749875, 1)	(3.5, 0)
medium	linear	(0, 0)	(1.749875, 0)	(3.5, 1)

Term Name	Shape/Par.	Definition Points (x, y)		
		(5.25, 0)	(7, 0)	
high	linear	(0, 0)	(3.5, 0)	(5.25, 1)
		(7, 1)		

Table 14: Definition Points of MBF "PricetoBookValue"

.14 Output Variable "Rating"

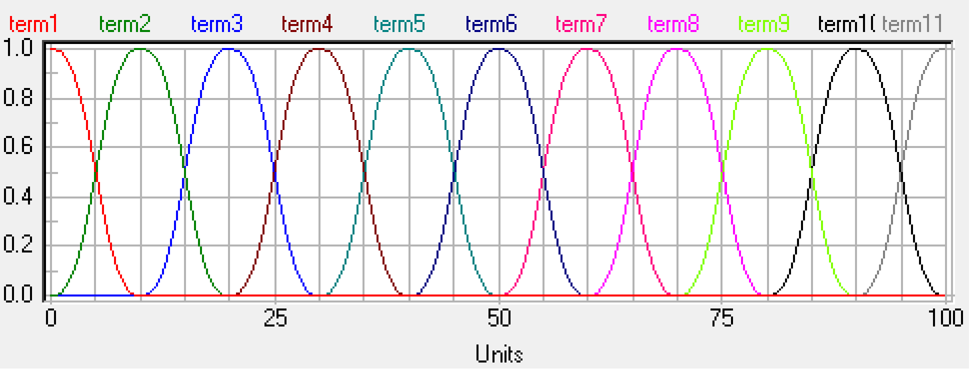


Figure 12: MBF of "Rating"

Term Name	Shape/Par.	Definition Points (x, y)		
term1	S-Shape/0.50	(0, 1)	(10, 0)	(100, 0)
term2	S-Shape/0.50	(0, 0)	(10, 1)	(20, 0)
		(100, 0)		
term3	S-Shape/0.50	(0, 0)	(10, 0)	(20, 1)
		(30, 0)	(100, 0)	
term4	S-Shape/0.50	(0, 0)	(20, 0)	(30, 1)
		(40, 0)	(100, 0)	
term5	S-Shape/0.50	(0, 0)	(30, 0)	(40, 1)
		(50, 0)	(100, 0)	
term6	S-Shape/0.50	(0, 0)	(40, 0)	(50, 1)
		(60, 0)	(100, 0)	
term7	S-Shape/0.50	(0, 0)	(50, 0)	(60, 1)
		(70, 0)	(100, 0)	
term8	S-Shape/0.50	(0, 0)	(60, 0)	(70, 1)
		(80, 0)	(100, 0)	
term9	S-Shape/0.50	(0, 0)	(70, 0)	(80, 1)
		(90, 0)	(100, 0)	
term10	S-Shape/0.50	(0, 0)	(80, 0)	(90, 1)
		(100, 0)		
term11	S-Shape/0.50	(0, 0)	(90, 0)	(100, 1)

Table 15: Definition Points of MBF "Rating"

.15 Intermediate Variable "country"

Term Name
low

medium
high

Table 16: Term Names of "country"

.16 Intermediate Variable "Efficiency"

Term Name
low
medium
high

Table 17: Term Names of "Efficiency"

.17 Intermediate Variable "firmspecific"

Term Name
low
medium
high

Table 18: Term Names of "firmspecific"

.18 Intermediate Variable "macroeco"

Term Name
low
medium
high

Table 19: Term Names of "macroeco"

.19 Intermediate Variable "Management"

Term Name
low
medium
high

Table 20: Term Names of "Management"

.20 Intermediate Variable "Privitization1"

Term Name

low medium high

Table 21: Term Names of "Privitization1"

.21 Intermediate Variable "sponsor"

Term Name
low medium high

Table 22: Term Names of "sponsor"

.22 Intermediate Variable "Sponsor"

Term Name
low medium high

Table 23: Term Names of "Sponsor"

.4 Rule Blocks

The rule blocks contain the control strategy of a fuzzy logic system. Each rule block confines all rules for the same context. A context is defined by the same input and output variables of the rules.

The rules' 'if' part describes the situation, for which the rules are designed. The 'then' part describes the response of the fuzzy system in this situation. The degree of support (DoS) is used to weigh each rule according to its importance.

The processing of the rules starts with calculating the 'if' part. The operator type of the rule block determines which method is used. The operator types MIN-MAX, MIN-AVG and GAMMA are available. The characteristic of each operator type is influenced by an additional parameter.

For example:

MIN-MAX, parameter value 0 = Minimum Operator (MIN)
MIN-MAX, parameter value 1 = Maximum Operator (MAX)
GAMMA, parameter value 0 = Product Operator (PROD)

The minimum operator is a generalization of the Boolean 'and'; the maximum operator is a generalization of the Boolean 'or'.

The fuzzy composition eventually combines the different rules to one conclusion. If the BSUM method is used all firing rules are evaluated, if the MAX method is used only the dominant rules are evaluated.

.1 Rule Block "Efficiency"

Parameter

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	BSUM
Number of Inputs:	3
Number of Outputs:	1
Number of Rules:	27

IF			THEN	
LoanDepositRatio	**NetInterestMargi**	**NPLratio**	**DoS**	**Efficiency**
term2	low	term2	1.00	medium
term2	low	term3	1.00	low
term2	low	term4	1.00	low
term2	medium	term2	1.00	medium
term2	medium	term3	1.00	medium
term2	medium	term4	1.00	medium
term2	high	term2	1.00	high
term2	high	term3	1.00	medium
term2	high	term4	1.00	medium
term3	low	term2	1.00	medium
term3	low	term3	1.00	medium
term3	low	term4	1.00	low
term3	medium	term2	1.00	medium
term3	medium	term3	1.00	medium
term3	medium	term4	1.00	medium
term3	high	term2	1.00	high
term3	high	term3	1.00	high
term3	high	term4	1.00	medium
term4	low	term2	1.00	medium
term4	low	term3	1.00	medium
term4	low	term4	1.00	low
term4	medium	term2	1.00	medium
term4	medium	term3	1.00	medium
term4	medium	term4	1.00	medium
term4	high	term2	1.00	high
term4	high	term3	1.00	high
term4	high	term4	1.00	medium

Table 24: Rules of the Rule Block "Efficiency"

.2 Rule Block "FinancialInstitutioRating"

Parameter

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	BSUM

Number of Inputs: 2
Number of Outputs: 1
Number of Rules: 9

IF		THEN	
Efficiency	**macroeco**	**DoS**	**Rating**
low	low	1.00	term2
low	medium	1.00	term5
low	high	1.00	term7
medium	low	1.00	term3
medium	medium	1.00	term6
medium	high	1.00	term9
high	low	1.00	term5
high	medium	1.00	term7
high	high	1.00	term10

Table 25: Rules of the Rule Block "FinancialInstitutioRating"

.3 Rule Block "MacroeconomicEnvironment"

Parameter

Aggregation: MINMAX
Parameter: 0.00
Result Aggregation: BSUM
Number of Inputs: 7
Number of Outputs: 1
Number of Rules: 648

IF							THEN	
DepositRate	**DevelopmentStatu**	**FXRgmFreFloat**	**FXRgmmanaged**	**GDP**	**Inflation**	**PricetoBookValue**	**DoS**	**macroeco**
low	Developing	low	freeFloat	term2	term2	low	1.00	low
low	Developing	low	freeFloat	term2	term2	medium	1.00	medium
low	Developing	low	freeFloat	term2	term2	high	1.00	medium
low	Developing	low	freeFloat	term2	term3	low	1.00	low
low	Developing	low	freeFloat	term2	term3	medium	1.00	medium
low	Developing	low	freeFloat	term2	term3	high	1.00	medium
low	Developing	low	freeFloat	term2	term4	low	1.00	low
low	Developing	low	freeFloat	term2	term4	medium	1.00	low
low	Developing	low	freeFloat	term2	term4	high	1.00	medium
low	Developing	low	freeFloat	term3	term2	low	1.00	medium
low	Developing	low	freeFloat	term3	term2	medium	1.00	medium
low	Developing	low	freeFloat	term3	term2	high	1.00	medium
low	Developing	low	freeFloat	term3	term3	low	1.00	low
low	Developing	low	freeFloat	term3	term3	medium	1.00	medium
low	Developing	low	freeFloat	term3	term3	high	1.00	medium
low	Developing	low	freeFloat	term3	term4	low	1.00	low
low	Developing	low	freeFloat	term3	term4	medium	1.00	medium
low	Developing	low	freeFloat	term3	term4	high	1.00	medium
low	Developing	low	freeFloat	term4	term2	low	1.00	medium
low	Developing	low	freeFloat	term4	term2	medium	1.00	medium
low	Developing	low	freeFloat	term4	term2	high	1.00	medium
low	Developing	low	freeFloat	term4	term3	low	1.00	medium

IF								THEN
low	Developing	low	freeFloat	term4	term3	medium	1.00	medium
low	Developing	low	freeFloat	term4	term3	high	1.00	medium
low	Developing	low	freeFloat	term4	term4	low	1.00	low
low	Developing	low	freeFloat	term4	term4	medium	1.00	medium
low	Developing	low	freeFloat	term4	term4	high	1.00	medium
low	Developing	low	Managned	term2	term2	low	1.00	medium
low	Developing	low	Managned	term2	term2	medium	1.00	medium
low	Developing	low	Managned	term2	term2	high	1.00	medium
low	Developing	low	Managned	term2	term3	low	1.00	medium
low	Developing	low	Managned	term2	term3	medium	1.00	medium
low	Developing	low	Managned	term2	term3	high	1.00	medium
low	Developing	low	Managned	term2	term4	low	1.00	medium
low	Developing	low	Managned	term2	term4	medium	1.00	medium
low	Developing	low	Managned	term2	term4	high	1.00	medium
low	Developing	low	Managned	term3	term2	low	1.00	medium
low	Developing	low	Managned	term3	term2	medium	1.00	medium
low	Developing	low	Managned	term3	term2	high	1.00	medium
low	Developing	low	Managned	term3	term3	low	1.00	medium
low	Developing	low	Managned	term3	term3	medium	1.00	medium
low	Developing	low	Managned	term3	term3	high	1.00	medium
low	Developing	low	Managned	term3	term4	low	1.00	medium
low	Developing	low	Managned	term3	term4	medium	1.00	medium
low	Developing	low	Managned	term3	term4	high	1.00	medium
low	Developing	low	Managned	term4	term2	low	1.00	medium
low	Developing	low	Managned	term4	term2	medium	1.00	medium
low	Developing	low	Managned	term4	term2	high	1.00	medium
low	Developing	low	Managned	term4	term3	low	1.00	medium
low	Developing	low	Managned	term4	term3	medium	1.00	medium
low	Developing	low	Managned	term4	term3	high	1.00	medium
low	Developing	low	Managned	term4	term4	low	1.00	medium
low	Developing	low	Managned	term4	term4	medium	1.00	medium
low	Developing	low	Managned	term4	term4	high	1.00	medium
low	Developing	high	freeFloat	term2	term2	low	1.00	low
low	Developing	high	freeFloat	term2	term2	medium	1.00	low
low	Developing	high	freeFloat	term2	term2	high	1.00	medium
low	Developing	high	freeFloat	term2	term3	low	1.00	low
low	Developing	high	freeFloat	term2	term3	medium	1.00	low
low	Developing	high	freeFloat	term2	term3	high	1.00	medium
low	Developing	high	freeFloat	term2	term4	low	1.00	low
low	Developing	high	freeFloat	term2	term4	medium	1.00	low
low	Developing	high	freeFloat	term2	term4	high	1.00	low
low	Developing	high	freeFloat	term3	term2	low	1.00	low
low	Developing	high	freeFloat	term3	term2	medium	1.00	low
low	Developing	high	freeFloat	term3	term2	high	1.00	medium
low	Developing	high	freeFloat	term3	term3	low	1.00	low
low	Developing	high	freeFloat	term3	term3	medium	1.00	low
low	Developing	high	freeFloat	term3	term3	high	1.00	medium
low	Developing	high	freeFloat	term3	term4	low	1.00	low
low	Developing	high	freeFloat	term3	term4	medium	1.00	low
low	Developing	high	freeFloat	term3	term4	high	1.00	medium
low	Developing	high	freeFloat	term4	term2	low	1.00	low
low	Developing	high	freeFloat	term4	term2	medium	1.00	medium
low	Developing	high	freeFloat	term4	term2	high	1.00	medium
low	Developing	high	freeFloat	term4	term3	low	1.00	low
low	Developing	high	freeFloat	term4	term3	medium	1.00	low
low	Developing	high	freeFloat	term4	term3	high	1.00	medium
low	Developing	high	freeFloat	term4	term4	low	1.00	low

IF							THEN	
low	Developing	high	freeFloat	term4	term4	medium	1.00	low
low	Developing	high	freeFloat	term4	term4	high	1.00	medium
low	Developing	high	Managned	term2	term2	low	1.00	medium
low	Developing	high	Managned	term2	term2	medium	1.00	medium
low	Developing	high	Managned	term2	term2	high	1.00	medium
low	Developing	high	Managned	term2	term3	low	1.00	low
low	Developing	high	Managned	term2	term3	medium	1.00	medium
low	Developing	high	Managned	term2	term3	high	1.00	medium
low	Developing	high	Managned	term2	term4	low	1.00	low
low	Developing	high	Managned	term2	term4	medium	1.00	medium
low	Developing	high	Managned	term2	term4	high	1.00	medium
low	Developing	high	Managned	term3	term2	low	1.00	medium
low	Developing	high	Managned	term3	term2	medium	1.00	medium
low	Developing	high	Managned	term3	term2	high	1.00	medium
low	Developing	high	Managned	term3	term3	low	1.00	medium
low	Developing	high	Managned	term3	term3	medium	1.00	medium
low	Developing	high	Managned	term3	term3	high	1.00	medium
low	Developing	high	Managned	term3	term4	low	1.00	low
low	Developing	high	Managned	term3	term4	medium	1.00	medium
low	Developing	high	Managned	term3	term4	high	1.00	medium
low	Developing	high	Managned	term4	term2	low	1.00	medium
low	Developing	high	Managned	term4	term2	medium	1.00	medium
low	Developing	high	Managned	term4	term2	high	1.00	medium
low	Developing	high	Managned	term4	term3	low	1.00	medium
low	Developing	high	Managned	term4	term3	medium	1.00	medium
low	Developing	high	Managned	term4	term3	high	1.00	medium
low	Developing	high	Managned	term4	term4	low	1.00	medium
low	Developing	high	Managned	term4	term4	medium	1.00	medium
low	Developing	high	Managned	term4	term4	high	1.00	medium
low	Developed	low	freeFloat	term2	term2	low	1.00	medium
low	Developed	low	freeFloat	term2	term2	medium	1.00	medium
low	Developed	low	freeFloat	term2	term2	high	1.00	medium
low	Developed	low	freeFloat	term2	term3	low	1.00	medium
low	Developed	low	freeFloat	term2	term3	medium	1.00	medium
low	Developed	low	freeFloat	term2	term3	high	1.00	medium
low	Developed	low	freeFloat	term2	term4	low	1.00	medium
low	Developed	low	freeFloat	term2	term4	medium	1.00	medium
low	Developed	low	freeFloat	term2	term4	high	1.00	medium
low	Developed	low	freeFloat	term3	term2	low	1.00	medium
low	Developed	low	freeFloat	term3	term2	medium	1.00	medium
low	Developed	low	freeFloat	term3	term2	high	1.00	medium
low	Developed	low	freeFloat	term3	term3	low	1.00	medium
low	Developed	low	freeFloat	term3	term3	medium	1.00	medium
low	Developed	low	freeFloat	term3	term3	high	1.00	medium
low	Developed	low	freeFloat	term3	term4	low	1.00	medium
low	Developed	low	freeFloat	term3	term4	medium	1.00	medium
low	Developed	low	freeFloat	term3	term4	high	1.00	medium
low	Developed	low	freeFloat	term4	term2	low	1.00	medium
low	Developed	low	freeFloat	term4	term2	medium	1.00	medium
low	Developed	low	freeFloat	term4	term2	high	1.00	medium
low	Developed	low	freeFloat	term4	term3	low	1.00	medium
low	Developed	low	freeFloat	term4	term3	medium	1.00	medium
low	Developed	low	freeFloat	term4	term3	high	1.00	medium
low	Developed	low	freeFloat	term4	term4	low	1.00	medium
low	Developed	low	freeFloat	term4	term4	medium	1.00	medium
low	Developed	low	freeFloat	term4	term4	high	1.00	medium
low	Developed	low	Managned	term2	term2	low	1.00	medium

IF							THEN	
low	Developed	low	Managned	term2	term2	medium	1.00	medium
low	Developed	low	Managned	term2	term2	high	1.00	high
low	Developed	low	Managned	term2	term3	low	1.00	medium
low	Developed	low	Managned	term2	term3	medium	1.00	medium
low	Developed	low	Managned	term2	term3	high	1.00	medium
low	Developed	low	Managned	term2	term4	low	1.00	medium
low	Developed	low	Managned	term2	term4	medium	1.00	medium
low	Developed	low	Managned	term2	term4	high	1.00	medium
low	Developed	low	Managned	term3	term2	low	1.00	medium
low	Developed	low	Managned	term3	term2	medium	1.00	medium
low	Developed	low	Managned	term3	term2	high	1.00	high
low	Developed	low	Managned	term3	term3	low	1.00	medium
low	Developed	low	Managned	term3	term3	medium	1.00	medium
low	Developed	low	Managned	term3	term3	high	1.00	high
low	Developed	low	Managned	term3	term4	low	1.00	medium
low	Developed	low	Managned	term3	term4	medium	1.00	medium
low	Developed	low	Managned	term3	term4	high	1.00	medium
low	Developed	low	Managned	term4	term2	low	1.00	medium
low	Developed	low	Managned	term4	term2	medium	1.00	high
low	Developed	low	Managned	term4	term2	high	1.00	high
low	Developed	low	Managned	term4	term3	low	1.00	medium
low	Developed	low	Managned	term4	term3	medium	1.00	medium
low	Developed	low	Managned	term4	term3	high	1.00	high
low	Developed	low	Managned	term4	term4	low	1.00	medium
low	Developed	low	Managned	term4	term4	medium	1.00	medium
low	Developed	low	Managned	term4	term4	high	1.00	high
low	Developed	high	freeFloat	term2	term2	low	1.00	medium
low	Developed	high	freeFloat	term2	term2	medium	1.00	medium
low	Developed	high	freeFloat	term2	term2	high	1.00	medium
low	Developed	high	freeFloat	term2	term3	low	1.00	medium
low	Developed	high	freeFloat	term2	term3	medium	1.00	medium
low	Developed	high	freeFloat	term2	term3	high	1.00	medium
low	Developed	high	freeFloat	term2	term4	low	1.00	medium
low	Developed	high	freeFloat	term2	term4	medium	1.00	medium
low	Developed	high	freeFloat	term2	term4	high	1.00	medium
low	Developed	high	freeFloat	term3	term2	low	1.00	medium
low	Developed	high	freeFloat	term3	term2	medium	1.00	medium
low	Developed	high	freeFloat	term3	term2	high	1.00	medium
low	Developed	high	freeFloat	term3	term3	low	1.00	medium
low	Developed	high	freeFloat	term3	term3	medium	1.00	medium
low	Developed	high	freeFloat	term3	term3	high	1.00	medium
low	Developed	high	freeFloat	term3	term4	low	1.00	medium
low	Developed	high	freeFloat	term3	term4	medium	1.00	medium
low	Developed	high	freeFloat	term3	term4	high	1.00	medium
low	Developed	high	freeFloat	term4	term2	low	1.00	medium
low	Developed	high	freeFloat	term4	term2	medium	1.00	medium
low	Developed	high	freeFloat	term4	term2	high	1.00	medium
low	Developed	high	freeFloat	term4	term3	low	1.00	medium
low	Developed	high	freeFloat	term4	term3	medium	1.00	medium
low	Developed	high	freeFloat	term4	term3	high	1.00	medium
low	Developed	high	freeFloat	term4	term4	low	1.00	medium
low	Developed	high	freeFloat	term4	term4	medium	1.00	medium
low	Developed	high	freeFloat	term4	term4	high	1.00	medium
low	Developed	high	Managned	term2	term2	low	1.00	medium
low	Developed	high	Managned	term2	term2	medium	1.00	medium
low	Developed	high	Managned	term2	term2	high	1.00	medium
low	Developed	high	Managned	term2	term3	low	1.00	medium

IF							THEN	
low	Developed	high	Managned	term2	term3	medium	1.00	medium
low	Developed	high	Managned	term2	term3	high	1.00	medium
low	Developed	high	Managned	term2	term4	low	1.00	medium
low	Developed	high	Managned	term2	term4	medium	1.00	medium
low	Developed	high	Managned	term2	term4	high	1.00	medium
low	Developed	high	Managned	term3	term2	low	1.00	medium
low	Developed	high	Managned	term3	term2	medium	1.00	medium
low	Developed	high	Managned	term3	term2	high	1.00	medium
low	Developed	high	Managned	term3	term3	low	1.00	medium
low	Developed	high	Managned	term3	term3	medium	1.00	medium
low	Developed	high	Managned	term3	term3	high	1.00	medium
low	Developed	high	Managned	term3	term4	low	1.00	medium
low	Developed	high	Managned	term3	term4	medium	1.00	medium
low	Developed	high	Managned	term3	term4	high	1.00	medium
low	Developed	high	Managned	term4	term2	low	1.00	medium
low	Developed	high	Managned	term4	term2	medium	1.00	medium
low	Developed	high	Managned	term4	term2	high	1.00	medium
low	Developed	high	Managned	term4	term3	low	1.00	medium
low	Developed	high	Managned	term4	term3	medium	1.00	medium
low	Developed	high	Managned	term4	term3	high	1.00	medium
low	Developed	high	Managned	term4	term4	low	1.00	medium
low	Developed	high	Managned	term4	term4	medium	1.00	medium
low	Developed	high	Managned	term4	term4	high	1.00	medium
term1	Developing	low	freeFloat	term2	term2	low	1.00	medium
term1	Developing	low	freeFloat	term2	term2	medium	1.00	medium
term1	Developing	low	freeFloat	term2	term2	high	1.00	medium
term1	Developing	low	freeFloat	term2	term3	low	1.00	low
term1	Developing	low	freeFloat	term2	term3	medium	1.00	medium
term1	Developing	low	freeFloat	term2	term3	high	1.00	medium
term1	Developing	low	freeFloat	term2	term4	low	1.00	low
term1	Developing	low	freeFloat	term2	term4	medium	1.00	medium
term1	Developing	low	freeFloat	term2	term4	high	1.00	medium
term1	Developing	low	freeFloat	term3	term2	low	1.00	medium
term1	Developing	low	freeFloat	term3	term2	medium	1.00	medium
term1	Developing	low	freeFloat	term3	term2	high	1.00	medium
term1	Developing	low	freeFloat	term3	term3	low	1.00	medium
term1	Developing	low	freeFloat	term3	term3	medium	1.00	medium
term1	Developing	low	freeFloat	term3	term3	high	1.00	medium
term1	Developing	low	freeFloat	term3	term4	low	1.00	low
term1	Developing	low	freeFloat	term3	term4	medium	1.00	medium
term1	Developing	low	freeFloat	term3	term4	high	1.00	medium
term1	Developing	low	freeFloat	term4	term2	low	1.00	medium
term1	Developing	low	freeFloat	term4	term2	medium	1.00	medium
term1	Developing	low	freeFloat	term4	term2	high	1.00	medium
term1	Developing	low	freeFloat	term4	term3	low	1.00	medium
term1	Developing	low	freeFloat	term4	term3	medium	1.00	medium
term1	Developing	low	freeFloat	term4	term3	high	1.00	medium
term1	Developing	low	freeFloat	term4	term4	low	1.00	medium
term1	Developing	low	freeFloat	term4	term4	medium	1.00	medium
term1	Developing	low	freeFloat	term4	term4	high	1.00	medium
term1	Developing	low	Managned	term2	term2	low	1.00	medium
term1	Developing	low	Managned	term2	term2	medium	1.00	medium
term1	Developing	low	Managned	term2	term2	high	1.00	medium
term1	Developing	low	Managned	term2	term3	low	1.00	medium
term1	Developing	low	Managned	term2	term3	medium	1.00	medium
term1	Developing	low	Managned	term2	term3	high	1.00	medium
term1	Developing	low	Managned	term2	term4	low	1.00	medium

IF								THEN
term1	Developing	low	Managned	term2	term4	medium	1.00	medium
term1	Developing	low	Managned	term2	term4	high	1.00	medium
term1	Developing	low	Managned	term3	term2	low	1.00	medium
term1	Developing	low	Managned	term3	term2	medium	1.00	medium
term1	Developing	low	Managned	term3	term2	high	1.00	medium
term1	Developing	low	Managned	term3	term3	low	1.00	medium
term1	Developing	low	Managned	term3	term3	medium	1.00	medium
term1	Developing	low	Managned	term3	term3	high	1.00	medium
term1	Developing	low	Managned	term3	term4	low	1.00	medium
term1	Developing	low	Managned	term3	term4	medium	1.00	medium
term1	Developing	low	Managned	term3	term4	high	1.00	medium
term1	Developing	low	Managned	term4	term2	low	1.00	medium
term1	Developing	low	Managned	term4	term2	medium	1.00	medium
term1	Developing	low	Managned	term4	term2	high	1.00	medium
term1	Developing	low	Managned	term4	term3	low	1.00	medium
term1	Developing	low	Managned	term4	term3	medium	1.00	medium
term1	Developing	low	Managned	term4	term3	high	1.00	medium
term1	Developing	low	Managned	term4	term4	low	1.00	medium
term1	Developing	low	Managned	term4	term4	medium	1.00	medium
term1	Developing	low	Managned	term4	term4	high	1.00	medium
term1	Developing	high	freeFloat	term2	term2	low	1.00	low
term1	Developing	high	freeFloat	term2	term2	medium	1.00	medium
term1	Developing	high	freeFloat	term2	term2	high	1.00	medium
term1	Developing	high	freeFloat	term2	term3	low	1.00	low
term1	Developing	high	freeFloat	term2	term3	medium	1.00	low
term1	Developing	high	freeFloat	term2	term3	high	1.00	medium
term1	Developing	high	freeFloat	term2	term4	low	1.00	low
term1	Developing	high	freeFloat	term2	term4	medium	1.00	low
term1	Developing	high	freeFloat	term2	term4	high	1.00	medium
term1	Developing	high	freeFloat	term3	term2	low	1.00	low
term1	Developing	high	freeFloat	term3	term2	medium	1.00	medium
term1	Developing	high	freeFloat	term3	term2	high	1.00	medium
term1	Developing	high	freeFloat	term3	term3	low	1.00	low
term1	Developing	high	freeFloat	term3	term3	medium	1.00	medium
term1	Developing	high	freeFloat	term3	term3	high	1.00	medium
term1	Developing	high	freeFloat	term3	term4	low	1.00	low
term1	Developing	high	freeFloat	term3	term4	medium	1.00	low
term1	Developing	high	freeFloat	term3	term4	high	1.00	medium
term1	Developing	high	freeFloat	term4	term2	low	1.00	medium
term1	Developing	high	freeFloat	term4	term2	medium	1.00	medium
term1	Developing	high	freeFloat	term4	term2	high	1.00	medium
term1	Developing	high	freeFloat	term4	term3	low	1.00	low
term1	Developing	high	freeFloat	term4	term3	medium	1.00	medium
term1	Developing	high	freeFloat	term4	term3	high	1.00	medium
term1	Developing	high	freeFloat	term4	term4	low	1.00	low
term1	Developing	high	freeFloat	term4	term4	medium	1.00	medium
term1	Developing	high	freeFloat	term4	term4	high	1.00	medium
term1	Developing	high	Managned	term2	term2	low	1.00	medium
term1	Developing	high	Managned	term2	term2	medium	1.00	medium
term1	Developing	high	Managned	term2	term2	high	1.00	medium
term1	Developing	high	Managned	term2	term3	low	1.00	medium
term1	Developing	high	Managned	term2	term3	medium	1.00	medium
term1	Developing	high	Managned	term2	term3	high	1.00	medium
term1	Developing	high	Managned	term2	term4	low	1.00	medium
term1	Developing	high	Managned	term2	term4	medium	1.00	medium
term1	Developing	high	Managned	term2	term4	high	1.00	medium
term1	Developing	high	Managned	term3	term2	low	1.00	medium

IF							THEN	
term1	Developing	high	Managned	term3	term2	medium	1.00	medium
term1	Developing	high	Managned	term3	term2	high	1.00	medium
term1	Developing	high	Managned	term3	term3	low	1.00	medium
term1	Developing	high	Managned	term3	term3	medium	1.00	medium
term1	Developing	high	Managned	term3	term3	high	1.00	medium
term1	Developing	high	Managned	term3	term4	low	1.00	medium
term1	Developing	high	Managned	term3	term4	medium	1.00	medium
term1	Developing	high	Managned	term3	term4	high	1.00	medium
term1	Developing	high	Managned	term4	term2	low	1.00	medium
term1	Developing	high	Managned	term4	term2	medium	1.00	medium
term1	Developing	high	Managned	term4	term2	high	1.00	medium
term1	Developing	high	Managned	term4	term3	low	1.00	medium
term1	Developing	high	Managned	term4	term3	medium	1.00	medium
term1	Developing	high	Managned	term4	term3	high	1.00	medium
term1	Developing	high	Managned	term4	term4	low	1.00	medium
term1	Developing	high	Managned	term4	term4	medium	1.00	medium
term1	Developing	high	Managned	term4	term4	high	1.00	medium
term1	Developed	low	freeFloat	term2	term2	low	1.00	medium
term1	Developed	low	freeFloat	term2	term2	medium	1.00	medium
term1	Developed	low	freeFloat	term2	term2	high	1.00	medium
term1	Developed	low	freeFloat	term2	term3	low	1.00	medium
term1	Developed	low	freeFloat	term2	term3	medium	1.00	medium
term1	Developed	low	freeFloat	term2	term3	high	1.00	medium
term1	Developed	low	freeFloat	term2	term4	low	1.00	medium
term1	Developed	low	freeFloat	term2	term4	medium	1.00	medium
term1	Developed	low	freeFloat	term2	term4	high	1.00	medium
term1	Developed	low	freeFloat	term3	term2	low	1.00	medium
term1	Developed	low	freeFloat	term3	term2	medium	1.00	medium
term1	Developed	low	freeFloat	term3	term2	high	1.00	medium
term1	Developed	low	freeFloat	term3	term3	low	1.00	medium
term1	Developed	low	freeFloat	term3	term3	medium	1.00	medium
term1	Developed	low	freeFloat	term3	term3	high	1.00	medium
term1	Developed	low	freeFloat	term3	term4	low	1.00	medium
term1	Developed	low	freeFloat	term3	term4	medium	1.00	medium
term1	Developed	low	freeFloat	term3	term4	high	1.00	medium
term1	Developed	low	freeFloat	term4	term2	low	1.00	medium
term1	Developed	low	freeFloat	term4	term2	medium	1.00	medium
term1	Developed	low	freeFloat	term4	term2	high	1.00	medium
term1	Developed	low	freeFloat	term4	term3	low	1.00	medium
term1	Developed	low	freeFloat	term4	term3	medium	1.00	medium
term1	Developed	low	freeFloat	term4	term3	high	1.00	medium
term1	Developed	low	freeFloat	term4	term4	low	1.00	medium
term1	Developed	low	freeFloat	term4	term4	medium	1.00	medium
term1	Developed	low	freeFloat	term4	term4	high	1.00	medium
term1	Developed	low	Managned	term2	term2	low	1.00	medium
term1	Developed	low	Managned	term2	term2	medium	1.00	medium
term1	Developed	low	Managned	term2	term2	high	1.00	high
term1	Developed	low	Managned	term2	term3	low	1.00	medium
term1	Developed	low	Managned	term2	term3	medium	1.00	medium
term1	Developed	low	Managned	term2	term3	high	1.00	high
term1	Developed	low	Managned	term2	term4	low	1.00	medium
term1	Developed	low	Managned	term2	term4	medium	1.00	medium
term1	Developed	low	Managned	term2	term4	high	1.00	medium
term1	Developed	low	Managned	term3	term2	low	1.00	medium
term1	Developed	low	Managned	term3	term2	medium	1.00	high
term1	Developed	low	Managned	term3	term2	high	1.00	high
term1	Developed	low	Managned	term3	term3	low	1.00	medium

IF							THEN	
term1	Developed	low	Managned	term3	term3	medium	1.00	medium
term1	Developed	low	Managned	term3	term3	high	1.00	high
term1	Developed	low	Managned	term3	term4	low	1.00	medium
term1	Developed	low	Managned	term3	term4	medium	1.00	medium
term1	Developed	low	Managned	term3	term4	high	1.00	high
term1	Developed	low	Managned	term4	term2	low	1.00	medium
term1	Developed	low	Managned	term4	term2	medium	1.00	high
term1	Developed	low	Managned	term4	term2	high	1.00	high
term1	Developed	low	Managned	term4	term3	low	1.00	medium
term1	Developed	low	Managned	term4	term3	medium	1.00	high
term1	Developed	low	Managned	term4	term3	high	1.00	high
term1	Developed	low	Managned	term4	term4	low	1.00	medium
term1	Developed	low	Managned	term4	term4	medium	1.00	medium
term1	Developed	low	Managned	term4	term4	high	1.00	high
term1	Developed	high	freeFloat	term2	term2	low	1.00	medium
term1	Developed	high	freeFloat	term2	term2	medium	1.00	medium
term1	Developed	high	freeFloat	term2	term2	high	1.00	medium
term1	Developed	high	freeFloat	term2	term3	low	1.00	medium
term1	Developed	high	freeFloat	term2	term3	medium	1.00	medium
term1	Developed	high	freeFloat	term2	term3	high	1.00	medium
term1	Developed	high	freeFloat	term2	term4	low	1.00	medium
term1	Developed	high	freeFloat	term2	term4	medium	1.00	medium
term1	Developed	high	freeFloat	term2	term4	high	1.00	medium
term1	Developed	high	freeFloat	term3	term2	low	1.00	medium
term1	Developed	high	freeFloat	term3	term2	medium	1.00	medium
term1	Developed	high	freeFloat	term3	term2	high	1.00	medium
term1	Developed	high	freeFloat	term3	term3	low	1.00	medium
term1	Developed	high	freeFloat	term3	term3	medium	1.00	medium
term1	Developed	high	freeFloat	term3	term3	high	1.00	medium
term1	Developed	high	freeFloat	term3	term4	low	1.00	medium
term1	Developed	high	freeFloat	term3	term4	medium	1.00	medium
term1	Developed	high	freeFloat	term3	term4	high	1.00	medium
term1	Developed	high	freeFloat	term4	term2	low	1.00	medium
term1	Developed	high	freeFloat	term4	term2	medium	1.00	medium
term1	Developed	high	freeFloat	term4	term2	high	1.00	medium
term1	Developed	high	freeFloat	term4	term3	low	1.00	medium
term1	Developed	high	freeFloat	term4	term3	medium	1.00	medium
term1	Developed	high	freeFloat	term4	term3	high	1.00	medium
term1	Developed	high	freeFloat	term4	term4	low	1.00	medium
term1	Developed	high	freeFloat	term4	term4	medium	1.00	medium
term1	Developed	high	freeFloat	term4	term4	high	1.00	medium
term1	Developed	high	Managned	term2	term2	low	1.00	medium
term1	Developed	high	Managned	term2	term2	medium	1.00	medium
term1	Developed	high	Managned	term2	term2	high	1.00	medium
term1	Developed	high	Managned	term2	term3	low	1.00	medium
term1	Developed	high	Managned	term2	term3	medium	1.00	medium
term1	Developed	high	Managned	term2	term3	high	1.00	medium
term1	Developed	high	Managned	term2	term4	low	1.00	medium
term1	Developed	high	Managned	term2	term4	medium	1.00	medium
term1	Developed	high	Managned	term2	term4	high	1.00	medium
term1	Developed	high	Managned	term3	term2	low	1.00	medium
term1	Developed	high	Managned	term3	term2	medium	1.00	medium
term1	Developed	high	Managned	term3	term2	high	1.00	high
term1	Developed	high	Managned	term3	term3	low	1.00	medium
term1	Developed	high	Managned	term3	term3	medium	1.00	medium
term1	Developed	high	Managned	term3	term3	high	1.00	medium
term1	Developed	high	Managned	term3	term4	low	1.00	medium

IF							THEN	
term1	Developed	high	Managned	term3	term4	medium	1.00	medium
term1	Developed	high	Managned	term3	term4	high	1.00	medium
term1	Developed	high	Managned	term4	term2	low	1.00	medium
term1	Developed	high	Managned	term4	term2	medium	1.00	medium
term1	Developed	high	Managned	term4	term2	high	1.00	high
term1	Developed	high	Managned	term4	term3	low	1.00	medium
term1	Developed	high	Managned	term4	term3	medium	1.00	medium
term1	Developed	high	Managned	term4	term3	high	1.00	high
term1	Developed	high	Managned	term4	term4	low	1.00	medium
term1	Developed	high	Managned	term4	term4	medium	1.00	medium
term1	Developed	high	Managned	term4	term4	high	1.00	medium
high	Developing	low	freeFloat	term2	term2	low	1.00	medium
high	Developing	low	freeFloat	term2	term2	medium	1.00	medium
high	Developing	low	freeFloat	term2	term2	high	1.00	medium
high	Developing	low	freeFloat	term2	term3	low	1.00	medium
high	Developing	low	freeFloat	term2	term3	medium	1.00	medium
high	Developing	low	freeFloat	term2	term3	high	1.00	medium
high	Developing	low	freeFloat	term2	term4	low	1.00	medium
high	Developing	low	freeFloat	term2	term4	medium	1.00	medium
high	Developing	low	freeFloat	term2	term4	high	1.00	medium
high	Developing	low	freeFloat	term3	term2	low	1.00	medium
high	Developing	low	freeFloat	term3	term2	medium	1.00	medium
high	Developing	low	freeFloat	term3	term2	high	1.00	medium
high	Developing	low	freeFloat	term3	term3	low	1.00	medium
high	Developing	low	freeFloat	term3	term3	medium	1.00	medium
high	Developing	low	freeFloat	term3	term3	high	1.00	medium
high	Developing	low	freeFloat	term3	term4	low	1.00	medium
high	Developing	low	freeFloat	term3	term4	medium	1.00	medium
high	Developing	low	freeFloat	term3	term4	high	1.00	medium
high	Developing	low	freeFloat	term4	term2	low	1.00	medium
high	Developing	low	freeFloat	term4	term2	medium	1.00	medium
high	Developing	low	freeFloat	term4	term2	high	1.00	medium
high	Developing	low	freeFloat	term4	term3	low	1.00	medium
high	Developing	low	freeFloat	term4	term3	medium	1.00	medium
high	Developing	low	freeFloat	term4	term3	high	1.00	medium
high	Developing	low	freeFloat	term4	term4	low	1.00	medium
high	Developing	low	freeFloat	term4	term4	medium	1.00	medium
high	Developing	low	freeFloat	term4	term4	high	1.00	medium
high	Developing	low	Managned	term2	term2	low	1.00	medium
high	Developing	low	Managned	term2	term2	medium	1.00	medium
high	Developing	low	Managned	term2	term2	high	1.00	medium
high	Developing	low	Managned	term2	term3	low	1.00	medium
high	Developing	low	Managned	term2	term3	medium	1.00	medium
high	Developing	low	Managned	term2	term3	high	1.00	medium
high	Developing	low	Managned	term2	term4	low	1.00	medium
high	Developing	low	Managned	term2	term4	medium	1.00	medium
high	Developing	low	Managned	term2	term4	high	1.00	medium
high	Developing	low	Managned	term3	term2	low	1.00	medium
high	Developing	low	Managned	term3	term2	medium	1.00	medium
high	Developing	low	Managned	term3	term2	high	1.00	medium
high	Developing	low	Managned	term3	term3	low	1.00	medium
high	Developing	low	Managned	term3	term3	medium	1.00	medium
high	Developing	low	Managned	term3	term3	high	1.00	medium
high	Developing	low	Managned	term3	term4	low	1.00	medium
high	Developing	low	Managned	term3	term4	medium	1.00	medium
high	Developing	low	Managned	term3	term4	high	1.00	medium
high	Developing	low	Managned	term4	term2	low	1.00	medium

IF							THEN	
high	Developing	low	Managned	term4	term2	medium	1.00	medium
high	Developing	low	Managned	term4	term2	high	1.00	medium
high	Developing	low	Managned	term4	term3	low	1.00	medium
high	Developing	low	Managned	term4	term3	medium	1.00	medium
high	Developing	low	Managned	term4	term3	high	1.00	medium
high	Developing	low	Managned	term4	term4	low	1.00	medium
high	Developing	low	Managned	term4	term4	medium	1.00	medium
high	Developing	low	Managned	term4	term4	high	1.00	medium
high	Developing	high	freeFloat	term2	term2	low	1.00	low
high	Developing	high	freeFloat	term2	term2	medium	1.00	medium
high	Developing	high	freeFloat	term2	term2	high	1.00	medium
high	Developing	high	freeFloat	term2	term3	low	1.00	low
high	Developing	high	freeFloat	term2	term3	medium	1.00	medium
high	Developing	high	freeFloat	term2	term3	high	1.00	medium
high	Developing	high	freeFloat	term2	term4	low	1.00	low
high	Developing	high	freeFloat	term2	term4	medium	1.00	low
high	Developing	high	freeFloat	term2	term4	high	1.00	medium
high	Developing	high	freeFloat	term3	term2	low	1.00	medium
high	Developing	high	freeFloat	term3	term2	medium	1.00	medium
high	Developing	high	freeFloat	term3	term2	high	1.00	medium
high	Developing	high	freeFloat	term3	term3	low	1.00	low
high	Developing	high	freeFloat	term3	term3	medium	1.00	medium
high	Developing	high	freeFloat	term3	term3	high	1.00	medium
high	Developing	high	freeFloat	term3	term4	low	1.00	low
high	Developing	high	freeFloat	term3	term4	medium	1.00	medium
high	Developing	high	freeFloat	term3	term4	high	1.00	medium
high	Developing	high	freeFloat	term4	term2	low	1.00	medium
high	Developing	high	freeFloat	term4	term2	medium	1.00	medium
high	Developing	high	freeFloat	term4	term2	high	1.00	medium
high	Developing	high	freeFloat	term4	term3	low	1.00	medium
high	Developing	high	freeFloat	term4	term3	medium	1.00	medium
high	Developing	high	freeFloat	term4	term3	high	1.00	medium
high	Developing	high	freeFloat	term4	term4	low	1.00	low
high	Developing	high	freeFloat	term4	term4	medium	1.00	medium
high	Developing	high	freeFloat	term4	term4	high	1.00	medium
high	Developing	high	Managned	term2	term2	low	1.00	medium
high	Developing	high	Managned	term2	term2	medium	1.00	medium
high	Developing	high	Managned	term2	term2	high	1.00	medium
high	Developing	high	Managned	term2	term3	low	1.00	medium
high	Developing	high	Managned	term2	term3	medium	1.00	medium
high	Developing	high	Managned	term2	term3	high	1.00	medium
high	Developing	high	Managned	term2	term4	low	1.00	medium
high	Developing	high	Managned	term2	term4	medium	1.00	medium
high	Developing	high	Managned	term2	term4	high	1.00	medium
high	Developing	high	Managned	term3	term2	low	1.00	medium
high	Developing	high	Managned	term3	term2	medium	1.00	medium
high	Developing	high	Managned	term3	term2	high	1.00	medium
high	Developing	high	Managned	term3	term3	low	1.00	medium
high	Developing	high	Managned	term3	term3	medium	1.00	medium
high	Developing	high	Managned	term3	term3	high	1.00	medium
high	Developing	high	Managned	term3	term4	low	1.00	medium
high	Developing	high	Managned	term3	term4	medium	1.00	medium
high	Developing	high	Managned	term3	term4	high	1.00	medium
high	Developing	high	Managned	term4	term2	low	1.00	medium
high	Developing	high	Managned	term4	term2	medium	1.00	medium
high	Developing	high	Managned	term4	term2	high	1.00	medium
high	Developing	high	Managned	term4	term3	low	1.00	medium

IF							THEN	
high	Developing	high	Managned	term4	term3	medium	1.00	medium
high	Developing	high	Managned	term4	term3	high	1.00	medium
high	Developing	high	Managned	term4	term4	low	1.00	medium
high	Developing	high	Managned	term4	term4	medium	1.00	medium
high	Developing	high	Managned	term4	term4	high	1.00	medium
high	Developed	low	freeFloat	term2	term2	low	1.00	medium
high	Developed	low	freeFloat	term2	term2	medium	1.00	medium
high	Developed	low	freeFloat	term2	term2	high	1.00	medium
high	Developed	low	freeFloat	term2	term3	low	1.00	medium
high	Developed	low	freeFloat	term2	term3	medium	1.00	medium
high	Developed	low	freeFloat	term2	term3	high	1.00	medium
high	Developed	low	freeFloat	term2	term4	low	1.00	medium
high	Developed	low	freeFloat	term2	term4	medium	1.00	medium
high	Developed	low	freeFloat	term2	term4	high	1.00	medium
high	Developed	low	freeFloat	term3	term2	low	1.00	medium
high	Developed	low	freeFloat	term3	term2	medium	1.00	medium
high	Developed	low	freeFloat	term3	term2	high	1.00	high
high	Developed	low	freeFloat	term3	term3	low	1.00	medium
high	Developed	low	freeFloat	term3	term3	medium	1.00	medium
high	Developed	low	freeFloat	term3	term3	high	1.00	medium
high	Developed	low	freeFloat	term3	term4	low	1.00	medium
high	Developed	low	freeFloat	term3	term4	medium	1.00	medium
high	Developed	low	freeFloat	term3	term4	high	1.00	medium
high	Developed	low	freeFloat	term4	term2	low	1.00	medium
high	Developed	low	freeFloat	term4	term2	medium	1.00	medium
high	Developed	low	freeFloat	term4	term2	high	1.00	high
high	Developed	low	freeFloat	term4	term3	low	1.00	medium
high	Developed	low	freeFloat	term4	term3	medium	1.00	medium
high	Developed	low	freeFloat	term4	term3	high	1.00	high
high	Developed	low	freeFloat	term4	term4	low	1.00	medium
high	Developed	low	freeFloat	term4	term4	medium	1.00	medium
high	Developed	low	freeFloat	term4	term4	high	1.00	medium
high	Developed	low	Managned	term2	term2	low	1.00	medium
high	Developed	low	Managned	term2	term2	medium	1.00	high
high	Developed	low	Managned	term2	term2	high	1.00	high
high	Developed	low	Managned	term2	term3	low	1.00	medium
high	Developed	low	Managned	term2	term3	medium	1.00	high
high	Developed	low	Managned	term2	term3	high	1.00	high
high	Developed	low	Managned	term2	term4	low	1.00	medium
high	Developed	low	Managned	term2	term4	medium	1.00	medium
high	Developed	low	Managned	term2	term4	high	1.00	high
high	Developed	low	Managned	term3	term2	low	1.00	medium
high	Developed	low	Managned	term3	term2	medium	1.00	high
high	Developed	low	Managned	term3	term2	high	1.00	high
high	Developed	low	Managned	term3	term3	low	1.00	medium
high	Developed	low	Managned	term3	term3	medium	1.00	high
high	Developed	low	Managned	term3	term3	high	1.00	high
high	Developed	low	Managned	term3	term4	low	1.00	medium
high	Developed	low	Managned	term3	term4	medium	1.00	high
high	Developed	low	Managned	term3	term4	high	1.00	high
high	Developed	low	Managned	term4	term2	low	1.00	high
high	Developed	low	Managned	term4	term2	medium	1.00	high
high	Developed	low	Managned	term4	term2	high	1.00	high
high	Developed	low	Managned	term4	term3	low	1.00	medium
high	Developed	low	Managned	term4	term3	medium	1.00	high
high	Developed	low	Managned	term4	term3	high	1.00	high
high	Developed	low	Managned	term4	term4	low	1.00	medium

IF								THEN
high	Developed	low	Managned	term4	term4	medium	1.00	high
high	Developed	low	Managned	term4	term4	high	1.00	high
high	Developed	high	freeFloat	term2	term2	low	1.00	medium
high	Developed	high	freeFloat	term2	term2	medium	1.00	medium
high	Developed	high	freeFloat	term2	term2	high	1.00	medium
high	Developed	high	freeFloat	term2	term3	low	1.00	medium
high	Developed	high	freeFloat	term2	term3	medium	1.00	medium
high	Developed	high	freeFloat	term2	term3	high	1.00	medium
high	Developed	high	freeFloat	term2	term4	low	1.00	medium
high	Developed	high	freeFloat	term2	term4	medium	1.00	medium
high	Developed	high	freeFloat	term2	term4	high	1.00	medium
high	Developed	high	freeFloat	term3	term2	low	1.00	medium
high	Developed	high	freeFloat	term3	term2	medium	1.00	medium
high	Developed	high	freeFloat	term3	term2	high	1.00	medium
high	Developed	high	freeFloat	term3	term3	low	1.00	medium
high	Developed	high	freeFloat	term3	term3	medium	1.00	medium
high	Developed	high	freeFloat	term3	term3	high	1.00	medium
high	Developed	high	freeFloat	term3	term4	low	1.00	medium
high	Developed	high	freeFloat	term3	term4	medium	1.00	medium
high	Developed	high	freeFloat	term3	term4	high	1.00	medium
high	Developed	high	freeFloat	term4	term2	low	1.00	medium
high	Developed	high	freeFloat	term4	term2	medium	1.00	medium
high	Developed	high	freeFloat	term4	term2	high	1.00	medium
high	Developed	high	freeFloat	term4	term3	low	1.00	medium
high	Developed	high	freeFloat	term4	term3	medium	1.00	medium
high	Developed	high	freeFloat	term4	term3	high	1.00	medium
high	Developed	high	freeFloat	term4	term4	low	1.00	medium
high	Developed	high	freeFloat	term4	term4	medium	1.00	medium
high	Developed	high	freeFloat	term4	term4	high	1.00	medium
high	Developed	high	Managned	term2	term2	low	1.00	medium
high	Developed	high	Managned	term2	term2	medium	1.00	medium
high	Developed	high	Managned	term2	term2	high	1.00	high
high	Developed	high	Managned	term2	term3	low	1.00	medium
high	Developed	high	Managned	term2	term3	medium	1.00	medium
high	Developed	high	Managned	term2	term3	high	1.00	medium
high	Developed	high	Managned	term2	term4	low	1.00	medium
high	Developed	high	Managned	term2	term4	medium	1.00	medium
high	Developed	high	Managned	term2	term4	high	1.00	medium
high	Developed	high	Managned	term3	term2	low	1.00	medium
high	Developed	high	Managned	term3	term2	medium	1.00	medium
high	Developed	high	Managned	term3	term2	high	1.00	high
high	Developed	high	Managned	term3	term3	low	1.00	medium
high	Developed	high	Managned	term3	term3	medium	1.00	medium
high	Developed	high	Managned	term3	term3	high	1.00	high
high	Developed	high	Managned	term3	term4	low	1.00	medium
high	Developed	high	Managned	term3	term4	medium	1.00	medium
high	Developed	high	Managned	term3	term4	high	1.00	medium
high	Developed	high	Managned	term4	term2	low	1.00	medium
high	Developed	high	Managned	term4	term2	medium	1.00	high
high	Developed	high	Managned	term4	term2	high	1.00	high
high	Developed	high	Managned	term4	term3	low	1.00	medium
high	Developed	high	Managned	term4	term3	medium	1.00	medium
high	Developed	high	Managned	term4	term3	high	1.00	high
high	Developed	high	Managned	term4	term4	low	1.00	medium
high	Developed	high	Managned	term4	term4	medium	1.00	medium
high	Developed	high	Managned	term4	term4	high	1.00	high

Table 26: Rules of the Rule Block "MacroeconomicEnvironment"

C.3.2 Very Large corporations's Rating Model

1 General Information

Author:	
Created:	Friday, February 08, 2013
Print Date:	Wednesday, June 24, 2015

Edition

Edition Name:	fuzzyTECH 5.54d Online Edition
Neuro Modul:	NeuroFuzzy add-on Module installed

.1 Table of Contents

.2 List of Figures

.3 List of Tables

.4 List of Abbreviations

Compute MBF	Compute Membership Function (Fuzzification Method)
Hyper CoM	Hyper Center of Maximum (Defuzzification Methode)
BSUM	Bounded Sum Fuzzy Operator for Result Aggregation
MIN	Fuzzy Operator for AND Aggregation
MAX	Fuzzy Operator for OR Aggregation
GAMMA	Compensatory Operator for Aggregation
PROD	Fuzzy Operator for Composition
LV	Linguistic Variable
MBF	Membership Function
RB	Rule Block

2 chapter4model-underwork-2

.1 Project Description

Input Variables	9
Output Variables	1
Intermediate Variables	3
Rule Blocks	4
Rules	288
Membership Functions	47

Table 1: Project Statistics

.2 System Structure

The system structure identifies the fuzzy logic inference flow from the input variables to the output variables. The fuzzification in the input interfaces translates analog inputs into fuzzy values. The fuzzy inference takes place in rule blocks which contain the linguistic control rules. The output of these rule blocks are linguistic variables. The defuzzification in the output interfaces translates them into analog variables.

The following figure shows the whole structure of this fuzzy system including input interfaces, rule blocks and output interfaces. The connecting lines symbolize the data flow.

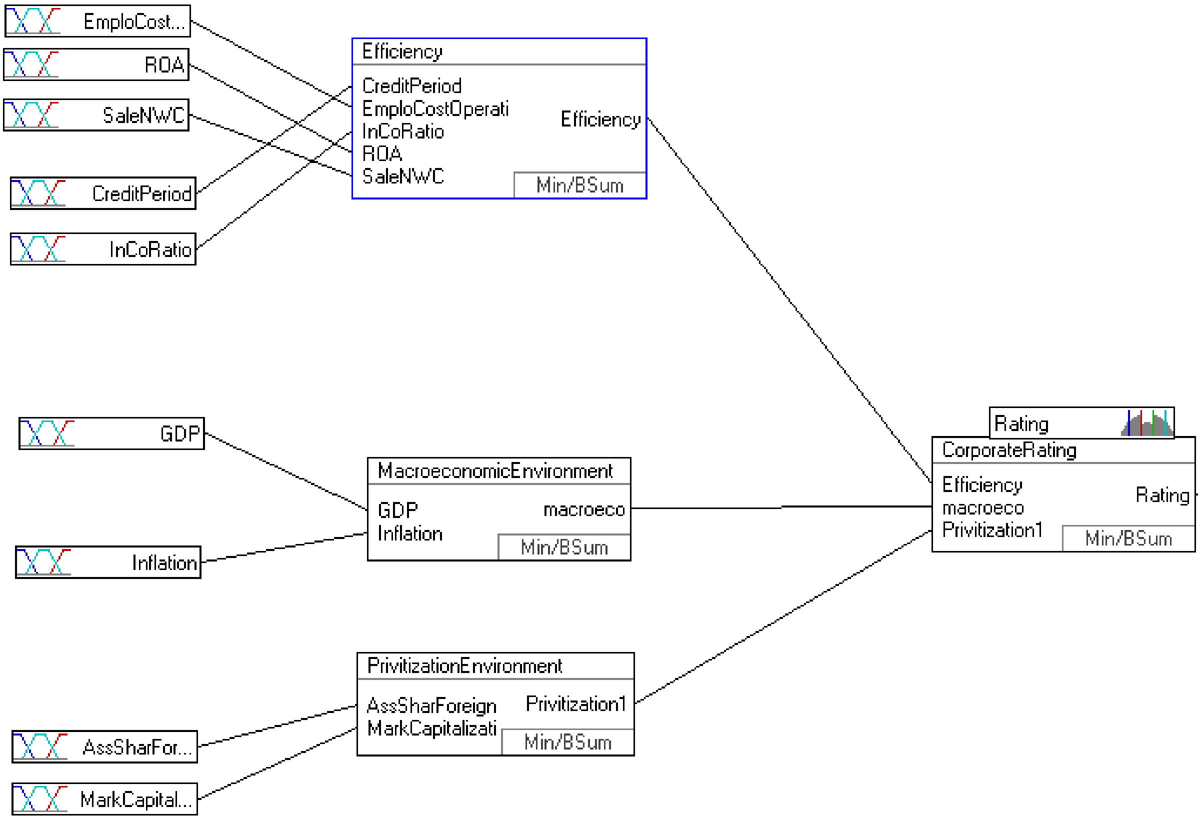
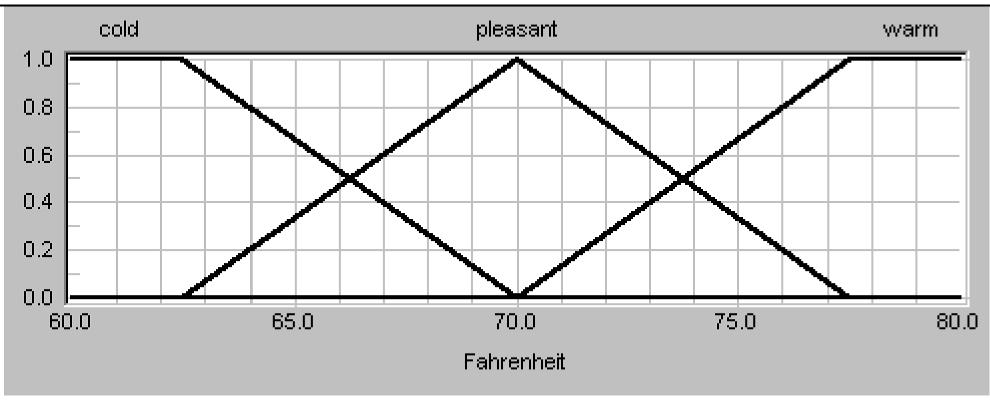


Figure 1: Structure of the Fuzzy Logic System

.3 Variables

This chapter contains the definition of all linguistic variables and of all membership functions.
Linguistic variables are used to translate real values into linguistic values. The possible values of a linguistic variable are not numbers but so called 'linguistic terms'.

For example:
To translate the real variable 'temperature' into a linguistic variable three terms, 'cold', 'pleasant' and 'warm' are defined. Depending on the current temperature level each of these terms describes the 'temperature' more or less well. Each term is defined by a membership function (MBF). Each membership function defines for any value of the input variable the associated degree of membership of the linguistic term. The membership functions of all terms of one linguistic variable are normally displayed in one graph. The following figure plots the membership functions of the three terms for the example 'temperature'.



Membership Function of 'temperature'

A 'temperature' of 66 °F is a member of the MBFs for the terms:

cold to the degree of 0.8
pleasant to the degree of 0.2
warm to the degree of 0.0

Linguistic variables have to be defined for all input, output and intermediate variables. The membership functions are defined using a few definition points only.

The following tables list all variables of the system as well as the respective fuzzification or defuzzification method. Also the properties of all base variables and the term names are listed.

.1 Inputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	AssSharForeign		Units	29	95	29	low medium high
2	CreditPeriod		Units	0	685	0	low medium high
3	EmploCostOperati		Units	0	5	0.5	low medium high
4	GDP		Units	0	30	0.5	term2 term3 term4
5	InCoRatio		Units	-69	954	0	low medium high
6	Inflation		Units	-2	12	0.5	term2 term3 term4
7	MarkCapitalizati		Units	5	183	5	low medium high
8	ROA		Units	-21	62	0	low medium high
9	SaleNWC		Units	-220	25543	0	term2

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
							term3 term4

Table 2: Variables of Group "Inputs"

Fuzzification Methods

Compute MBF | Look up MBF
Categorical Variable | Display
Fuzzy Input

.2 Outputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
10	Rating		Units	0	100	0	term1 term2 term3 term4 term5 term6 term7 term8 term9 term10 term11

Table 3: Variables of Group "Outputs"

Defuzzification Methods

Center of Maximum (CoM) | Mean of Maximum (MoM)
Center of Area (CoA) | Hyper CoM
Fuzzy Output | Force

The default value of an output variable is used if no rule is firing for this variable.Different methods can be used for the defuzzification, resulting either into the 'most plausible result' or the 'best compromise'.

The 'best compromise' is produced by the methods:

CoM (Center of Maximum)
CoA (Center of Area)
CoA BSUM, a version especially for efficient VLSI implementations

The 'most plausible result is produced by the methods:

MoM (Mean of Maximum)
MoM BSUM, a version especially for efficient VLSI implementations

.3 Intermediates

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
11	Efficiency		-	-	-	-	low medium high
12	macroeco		-	-	-	-	low medium high
13	Privitization1		-	-	-	-	low medium high

Table 4: Variables of Group "Intermediates"

.4 Input Variable "AssSharForeign"

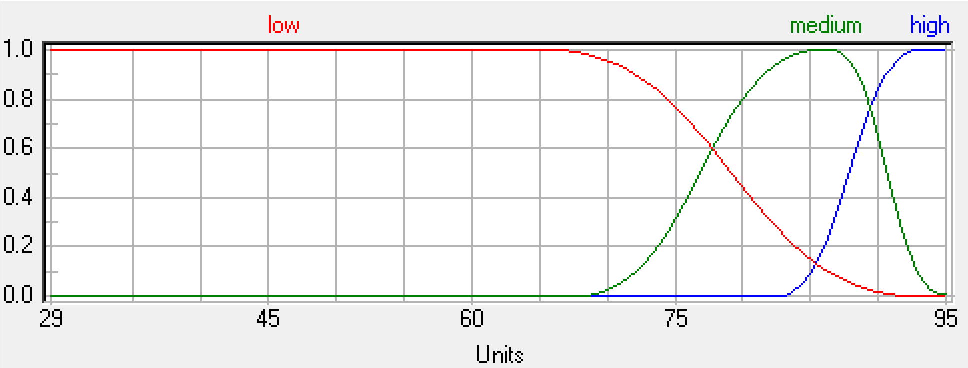


Figure 2: MBF of "AssSharForeign"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(29, 1) (95, 0)	(64.82125, 1)	(93.59125, 0)
medium	S-Shape/0.50	(29, 0) (95, 0.00934)	(67.36, 0) (95, 0)	(86.25625, 1)
high	S-Shape/0.50	(29, 0) (95, 1)	(82.30875, 0)	(93.3075, 1)

Table 5: Definition Points of MBF "AssSharForeign"

.5 Input Variable "CreditPeriod"

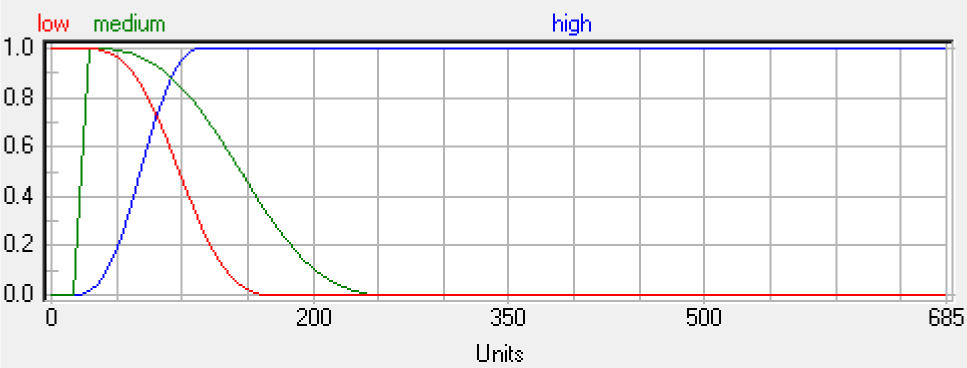


Figure 3: MBF of "CreditPeriod"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(0, 1) (685, 0)	(26.35, 1)	(169.775, 0)
medium	S-Shape/0.50	(0, 0) (260.525, 0)	(17.5625, 0) (685, 0)	(29.275, 1)
high	S-Shape/0.50	(0, 0) (685, 1)	(17.5625, 0)	(120.025, 1)

Table 6: Definition Points of MBF "CreditPeriod"

.6 Input Variable "EmploCostOperati"

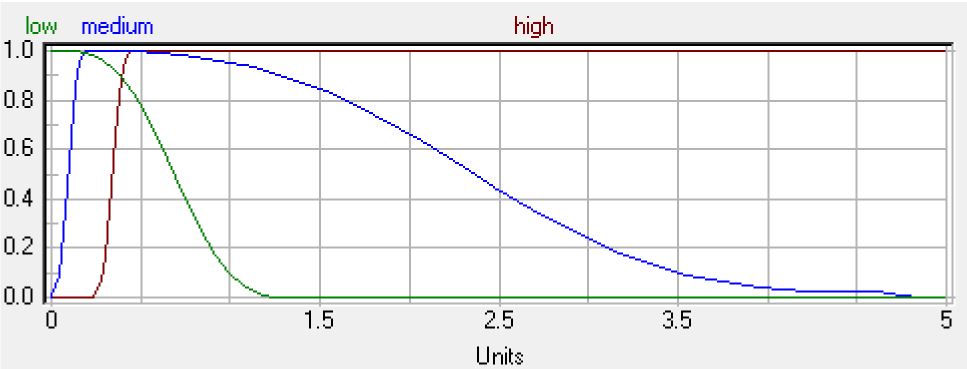


Figure 4: MBF of "EmploCostOperati"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(0, 1) (5, 0)	(0.0641, 1)	(1.3034, 0)
medium	S-Shape/0.50	(0, 0) (4.4873, 0.02804)	(0, 0.00934) (5, 0)	(0.1923, 1)
high	S-Shape/0.50	(0, 0) (5, 1)	(0.235, 0)	(0.4487, 1)

Table 7: Definition Points of MBF "EmploCostOperati"

.7 Input Variable "GDP"

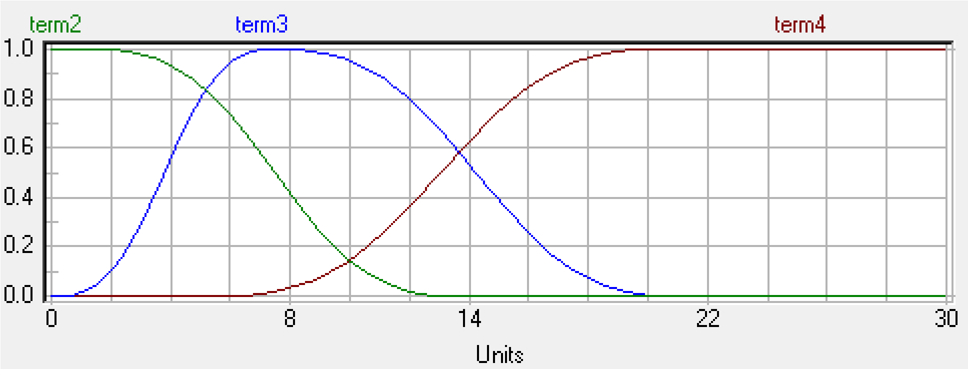


Figure 5: MBF of "GDP"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(0, 1) (30, 0)	(1.41, 1)	(13.59, 0)
term3	S-Shape/0.50	(0, 0) (21.026, 0)	(0.1285, 0) (30, 0)	(7.436, 1)
term4	S-Shape/0.50	(0, 0) (30, 1)	(5.641, 0)	(20.3845, 1)

Table 8: Definition Points of MBF "GDP"

.8 Input Variable "InCoRatio"

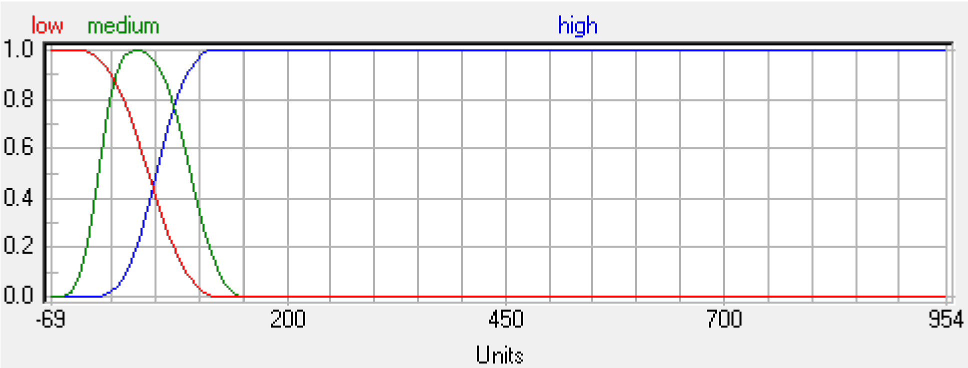


Figure 6: MBF of "InCoRatio"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(-69, 1) (954, 0)	(-43.82, 1)	(127.74, 0)
medium	S-Shape/0.50	(-69, 0) (156.06, 0)	(-54.86, 0) (954, 0)	(25.44, 1)
high	S-Shape/0.50	(-69, 0) (954, 1)	(-18.66, 0.00182)	(121.46, 1)

Table 9: Definition Points of MBF "InCoRatio"

.9 Input Variable "Inflation"

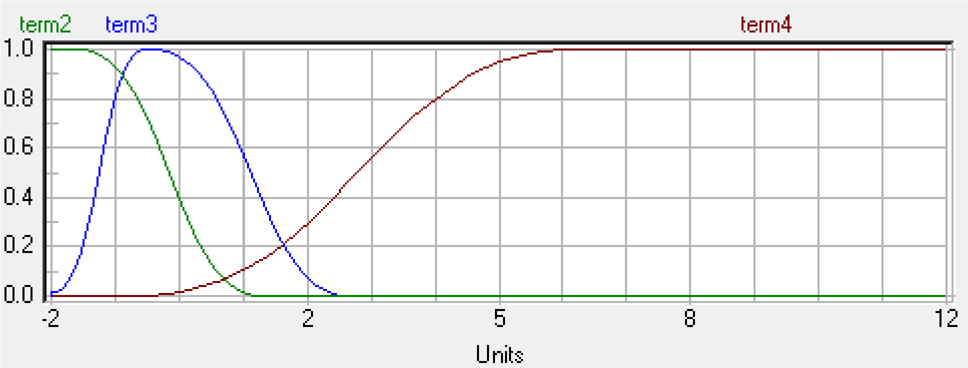


Figure 7: MBF of "Inflation"

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(-2, 1) (12, 0)	(-1.641, 1)	(1.3505, 0)
term3	S-Shape/0.50	(-2, 0) (2.72675, 0)	(-2, 0.01828) (12, 0)	(-0.5045, 1)
term4	S-Shape/0.50	(-2, 0) (12, 1)	(-0.88, 0.00182)	(6.43575, 1)

Table 10: Definition Points of MBF "Inflation"

.10 Input Variable "MarkCapitalizati"

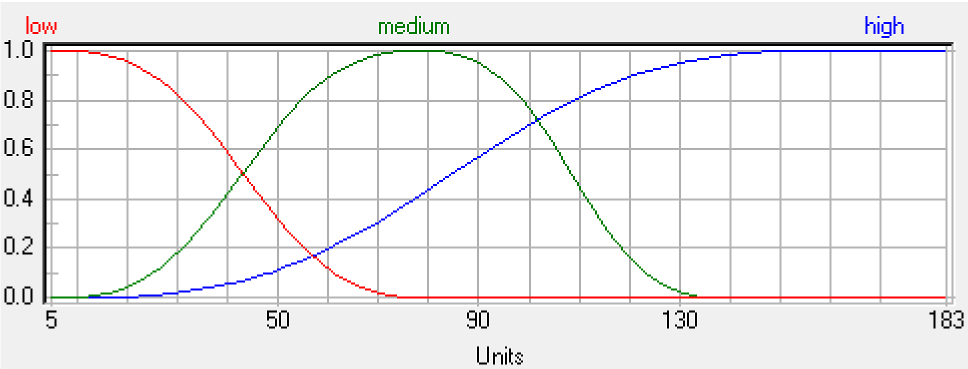


Figure 8: MBF of "MarkCapitalizati"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(5, 1) (183, 0)	(7.19, 1)	(79.48, 0)
medium	S-Shape/0.50	(5, 0) (138.5, 0)	(6.915, 0) (183, 0)	(78.785, 1)

Term Name	Shape/Par.	Definition Points (x, y)		
high	S-Shape/0.50	(5, 0) (183, 1)	(11.03, 0)	(157.9, 1)

Table 11: Definition Points of MBF "MarkCapitalizati"

.11 Input Variable "ROA"

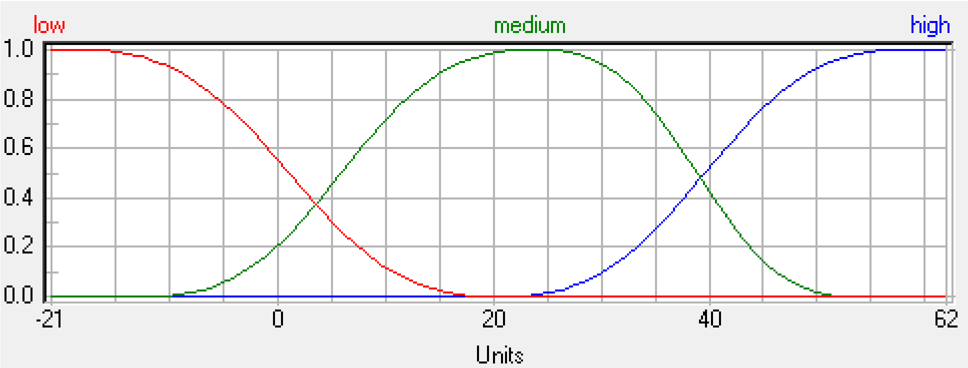


Figure 9: MBF of "ROA"

Term Name	Shape/Par.	Definition Points (x, y)		
low	S-Shape/0.50	(-21, 1) (62, 0)	(-18.518, 1)	(20.5, 0)
medium	S-Shape/0.50	(-21, 0) (53.7, 0)	(-12.486, 0) (62, 0)	(24.046, 1)
high	S-Shape/0.50	(-21, 0) (62, 1)	(20.5, 0)	(58.454, 1)

Table 12: Definition Points of MBF "ROA"

.12 Input Variable "SaleNWC"

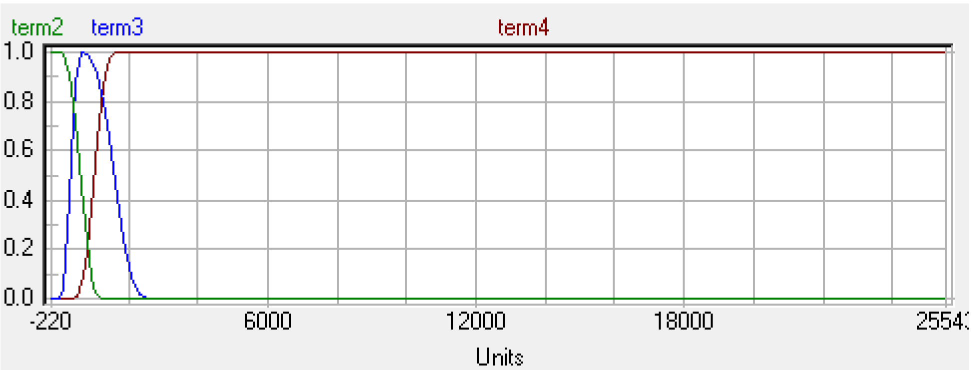


Figure 10: MBF of "SaleNWC"

Term Name	Shape/Par.	Definition Points (x, y)

Term Name	Shape/Par.	Definition Points (x, y)		
term2	S-Shape/0.50	(-220, 1) (25543, 0)	(0.5, 1)	(1211, 0)
term3	S-Shape/0.50	(-220, 0) (2532.5, 0)	(0.5, 0) (25543, 0)	(660.5, 1)
term4	S-Shape/0.50	(-220, 0) (25543, 1)	(440.5, 0)	(1652, 1)

Table 13: Definition Points of MBF "SaleNWC"

.13 Output Variable "Rating"

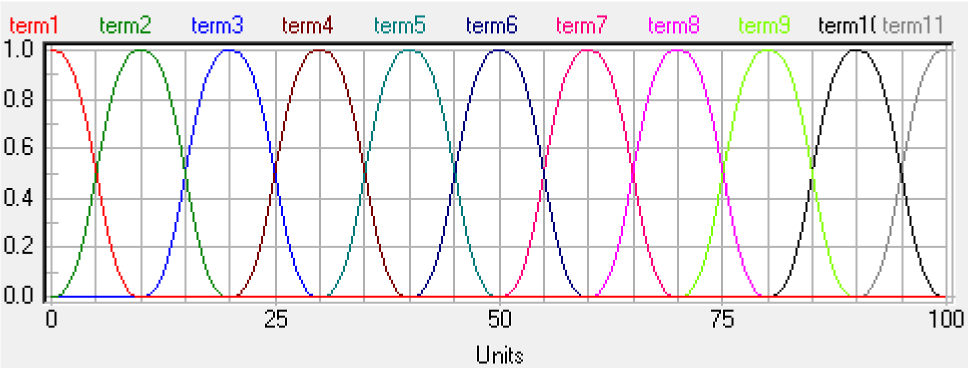


Figure 11: MBF of "Rating"

Term Name	Shape/Par.	Definition Points (x, y)		
term1	S-Shape/0.50	(0, 1)	(10, 0)	(100, 0)
term2	S-Shape/0.50	(0, 0) (100, 0)	(10, 1)	(20, 0)
term3	S-Shape/0.50	(0, 0) (30, 0)	(10, 0) (100, 0)	(20, 1)
term4	S-Shape/0.50	(0, 0) (40, 0)	(20, 0) (100, 0)	(30, 1)
term5	S-Shape/0.50	(0, 0) (50, 0)	(30, 0) (100, 0)	(40, 1)
term6	S-Shape/0.50	(0, 0) (60, 0)	(40, 0) (100, 0)	(50, 1)
term7	S-Shape/0.50	(0, 0) (70, 0)	(50, 0) (100, 0)	(60, 1)
term8	S-Shape/0.50	(0, 0) (80, 0)	(60, 0) (100, 0)	(70, 1)
term9	S-Shape/0.50	(0, 0) (90, 0)	(70, 0) (100, 0)	(80, 1)
term10	S-Shape/0.50	(0, 0) (100, 0)	(80, 0)	(90, 1)
term11	S-Shape/0.50	(0, 0)	(90, 0)	(100, 1)

Table 14: Definition Points of MBF "Rating"

.14 Intermediate Variable "Efficiency"

Term Name
low medium high

Table 15: Term Names of "Efficiency"

.15 Intermediate Variable "macroeco"

Term Name
low medium high

Table 16: Term Names of "macroeco"

.16 Intermediate Variable "Privitization1"

Term Name
low medium high

Table 17: Term Names of "Privitization1"

.4 Rule Blocks

The rule blocks contain the control strategy of a fuzzy logic system. Each rule block confines all rules for the same context. A context is defined by the same input and output variables of the rules.

The rules' 'if' part describes the situation, for which the rules are designed. The 'then' part describes the response of the fuzzy system in this situation. The degree of support (DoS) is used to weigh each rule according to its importance.

The processing of the rules starts with calculating the 'if' part. The operator type of the rule block determines which method is used. The operator types MIN-MAX, MIN-AVG and GAMMA are available. The characteristic of each operator type is influenced by an additional parameter.

For example:

MIN-MAX, parameter value 0	=	Minimum Operator (MIN)
MIN-MAX, parameter value 1	=	Maximum Operator (MAX)
GAMMA, parameter value 0	=	Product Operator (PROD)

The minimum operator is a generalization of the Boolean 'and'; the maximum operator is a generalization of the Boolean 'or'.

The fuzzy composition eventually combines the different rules to one conclusion. If the BSUM method is used all firing rules are evaluated, if the MAX method is used only the dominant rules are evaluated.

.1 Rule Block "CorporateRating"

Parameter

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	BSUM
Number of Inputs:	3
Number of Outputs:	1
Number of Rules:	27

IF			THEN	
Efficiency	**macroeco**	**Privitization1**	**DoS**	**Rating**
low	low	low	1.00	term1
low	low	medium	1.00	term2
low	low	high	1.00	term4
low	medium	low	1.00	term2
low	medium	medium	1.00	term4
low	medium	high	1.00	term6
low	high	low	1.00	term4
low	high	medium	1.00	term6
low	high	high	1.00	term8
medium	low	low	1.00	term2
medium	low	medium	1.00	term4
medium	low	high	1.00	term6
medium	medium	low	1.00	term4
medium	medium	medium	1.00	term6
medium	medium	high	1.00	term8
medium	high	low	1.00	term6
medium	high	medium	1.00	term8
medium	high	high	1.00	term10
high	low	low	1.00	term4
high	low	medium	1.00	term6
high	low	high	1.00	term8
high	medium	low	1.00	term6
high	medium	medium	1.00	term8
high	medium	high	1.00	term10
high	high	low	1.00	term8
high	high	medium	1.00	term10
high	high	high	1.00	term11

Table 18: Rules of the Rule Block "CorporateRating"

.2 Rule Block "Efficiency"

Parameter

Aggregation: MINMAX
Parameter: 0.00
Result Aggregation: BSUM
Number of Inputs: 5
Number of Outputs: 1
Number of Rules: 243

IF					THEN	
CreditPeriod	**EmploCostOperati**	**InCoRatio**	**ROA**	**SaleNWC**	**DoS**	**Efficiency**
low	low	low	low	term2	1.00	low
low	low	low	low	term3	1.00	medium
low	low	low	low	term4	1.00	medium
low	low	low	medium	term2	1.00	medium
low	low	low	medium	term3	1.00	medium
low	low	low	medium	term4	1.00	medium
low	low	low	high	term2	1.00	medium
low	low	low	high	term3	1.00	medium
low	low	low	high	term4	1.00	medium
low	low	medium	low	term2	1.00	medium
low	low	medium	low	term3	1.00	medium
low	low	medium	low	term4	1.00	medium
low	low	medium	medium	term2	1.00	medium
low	low	medium	medium	term3	1.00	medium
low	low	medium	medium	term4	1.00	medium
low	low	medium	high	term2	1.00	medium
low	low	medium	high	term3	1.00	medium
low	low	medium	high	term4	1.00	high
low	low	high	low	term2	1.00	medium
low	low	high	low	term3	1.00	medium
low	low	high	low	term4	1.00	medium
low	low	high	medium	term2	1.00	medium
low	low	high	medium	term3	1.00	medium
low	low	high	medium	term4	1.00	high
low	low	high	high	term2	1.00	medium
low	low	high	high	term3	1.00	high
low	low	high	high	term4	1.00	high
low	medium	low	low	term2	1.00	low
low	medium	low	low	term3	1.00	low
low	medium	low	low	term4	1.00	medium
low	medium	low	medium	term2	1.00	low
low	medium	low	medium	term3	1.00	medium
low	medium	low	medium	term4	1.00	medium
low	medium	low	high	term2	1.00	medium
low	medium	low	high	term3	1.00	medium
low	medium	low	high	term4	1.00	medium
low	medium	medium	low	term2	1.00	low
low	medium	medium	low	term3	1.00	medium
low	medium	medium	low	term4	1.00	medium
low	medium	medium	medium	term2	1.00	medium
low	medium	medium	medium	term3	1.00	medium
low	medium	medium	medium	term4	1.00	medium
low	medium	medium	high	term2	1.00	medium
low	medium	medium	high	term3	1.00	medium
low	medium	medium	high	term4	1.00	medium
low	medium	high	low	term2	1.00	medium

IF					THEN	
low	medium	high	low	term3	1.00	medium
low	medium	high	low	term4	1.00	medium
low	medium	high	medium	term2	1.00	medium
low	medium	high	medium	term3	1.00	medium
low	medium	high	medium	term4	1.00	medium
low	medium	high	high	term2	1.00	medium
low	medium	high	high	term3	1.00	medium
low	medium	high	high	term4	1.00	high
low	high	low	low	term2	1.00	low
low	high	low	low	term3	1.00	low
low	high	low	low	term4	1.00	low
low	high	low	medium	term2	1.00	low
low	high	low	medium	term3	1.00	low
low	high	low	medium	term4	1.00	medium
low	high	low	high	term2	1.00	low
low	high	low	high	term3	1.00	medium
low	high	low	high	term4	1.00	medium
low	high	medium	low	term2	1.00	low
low	high	medium	low	term3	1.00	low
low	high	medium	low	term4	1.00	medium
low	high	medium	medium	term2	1.00	low
low	high	medium	medium	term3	1.00	medium
low	high	medium	medium	term4	1.00	medium
low	high	medium	high	term2	1.00	medium
low	high	medium	high	term3	1.00	medium
low	high	medium	high	term4	1.00	medium
low	high	high	low	term2	1.00	low
low	high	high	low	term3	1.00	medium
low	high	high	low	term4	1.00	medium
low	high	high	medium	term2	1.00	medium
low	high	high	medium	term3	1.00	medium
low	high	high	medium	term4	1.00	medium
low	high	high	high	term2	1.00	medium
low	high	high	high	term3	1.00	medium
low	high	high	high	term4	1.00	medium
medium	low	low	low	term2	1.00	medium
medium	low	low	low	term3	1.00	medium
medium	low	low	low	term4	1.00	medium
medium	low	low	medium	term2	1.00	medium
medium	low	low	medium	term3	1.00	medium
medium	low	low	medium	term4	1.00	medium
medium	low	low	high	term2	1.00	medium
medium	low	low	high	term3	1.00	medium
medium	low	low	high	term4	1.00	high
medium	low	medium	low	term2	1.00	medium
medium	low	medium	low	term3	1.00	medium
medium	low	medium	low	term4	1.00	medium
medium	low	medium	medium	term2	1.00	medium
medium	low	medium	medium	term3	1.00	medium
medium	low	medium	medium	term4	1.00	medium
medium	low	medium	high	term2	1.00	medium
medium	low	medium	high	term3	1.00	high
medium	low	medium	high	term4	1.00	high
medium	low	high	low	term2	1.00	medium
medium	low	high	low	term3	1.00	medium
medium	low	high	low	term4	1.00	medium
medium	low	high	medium	term2	1.00	medium

IF					THEN	
medium	low	high	medium	term3	1.00	medium
medium	low	high	medium	term4	1.00	high
medium	low	high	high	term2	1.00	medium
medium	low	high	high	term3	1.00	high
medium	low	high	high	term4	1.00	high
medium	medium	low	low	term2	1.00	low
medium	medium	low	low	term3	1.00	medium
medium	medium	low	low	term4	1.00	medium
medium	medium	low	medium	term2	1.00	medium
medium	medium	low	medium	term3	1.00	medium
medium	medium	low	medium	term4	1.00	medium
medium	medium	low	high	term2	1.00	medium
medium	medium	low	high	term3	1.00	medium
medium	medium	low	high	term4	1.00	medium
medium	medium	medium	low	term2	1.00	low
medium	medium	medium	low	term3	1.00	medium
medium	medium	medium	low	term4	1.00	medium
medium	medium	medium	medium	term2	1.00	medium
medium	medium	medium	medium	term3	1.00	medium
medium	medium	medium	medium	term4	1.00	medium
medium	medium	medium	high	term2	1.00	medium
medium	medium	medium	high	term3	1.00	medium
medium	medium	medium	high	term4	1.00	high
medium	medium	high	low	term2	1.00	medium
medium	medium	high	low	term3	1.00	medium
medium	medium	high	low	term4	1.00	medium
medium	medium	high	medium	term2	1.00	medium
medium	medium	high	medium	term3	1.00	medium
medium	medium	high	medium	term4	1.00	medium
medium	medium	high	high	term2	1.00	medium
medium	medium	high	high	term3	1.00	medium
medium	medium	high	high	term4	1.00	high
medium	high	low	low	term2	1.00	low
medium	high	low	low	term3	1.00	low
medium	high	low	low	term4	1.00	medium
medium	high	low	medium	term2	1.00	low
medium	high	low	medium	term3	1.00	medium
medium	high	low	medium	term4	1.00	medium
medium	high	low	high	term2	1.00	medium
medium	high	low	high	term3	1.00	medium
medium	high	low	high	term4	1.00	medium
medium	high	medium	low	term2	1.00	low
medium	high	medium	low	term3	1.00	low
medium	high	medium	low	term4	1.00	medium
medium	high	medium	medium	term2	1.00	medium
medium	high	medium	medium	term3	1.00	medium
medium	high	medium	medium	term4	1.00	medium
medium	high	medium	high	term2	1.00	medium
medium	high	medium	high	term3	1.00	medium
medium	high	medium	high	term4	1.00	medium
medium	high	high	low	term2	1.00	low
medium	high	high	low	term3	1.00	medium
medium	high	high	low	term4	1.00	medium
medium	high	high	medium	term2	1.00	medium
medium	high	high	medium	term3	1.00	medium
medium	high	high	medium	term4	1.00	medium
medium	high	high	high	term2	1.00	medium

IF					THEN	
medium	high	high	high	term3	1.00	medium
medium	high	high	high	term4	1.00	medium
high	low	low	low	term2	1.00	medium
high	low	low	low	term3	1.00	medium
high	low	low	low	term4	1.00	medium
high	low	low	medium	term2	1.00	medium
high	low	low	medium	term3	1.00	medium
high	low	low	medium	term4	1.00	medium
high	low	low	high	term2	1.00	medium
high	low	low	high	term3	1.00	medium
high	low	low	high	term4	1.00	high
high	low	medium	low	term2	1.00	medium
high	low	medium	low	term3	1.00	medium
high	low	medium	low	term4	1.00	medium
high	low	medium	medium	term2	1.00	medium
high	low	medium	medium	term3	1.00	medium
high	low	medium	medium	term4	1.00	high
high	low	medium	high	term2	1.00	medium
high	low	medium	high	term3	1.00	high
high	low	medium	high	term4	1.00	high
high	low	high	low	term2	1.00	medium
high	low	high	low	term3	1.00	medium
high	low	high	low	term4	1.00	high
high	low	high	medium	term2	1.00	medium
high	low	high	medium	term3	1.00	high
high	low	high	medium	term4	1.00	high
high	low	high	high	term2	1.00	high
high	low	high	high	term3	1.00	high
high	low	high	high	term4	1.00	high
high	medium	low	low	term2	1.00	low
high	medium	low	low	term3	1.00	medium
high	medium	low	low	term4	1.00	medium
high	medium	low	medium	term2	1.00	medium
high	medium	low	medium	term3	1.00	medium
high	medium	low	medium	term4	1.00	medium
high	medium	low	high	term2	1.00	medium
high	medium	low	high	term3	1.00	medium
high	medium	low	high	term4	1.00	medium
high	medium	medium	low	term2	1.00	medium
high	medium	medium	low	term3	1.00	medium
high	medium	medium	low	term4	1.00	medium
high	medium	medium	medium	term2	1.00	medium
high	medium	medium	medium	term3	1.00	medium
high	medium	medium	medium	term4	1.00	medium
high	medium	medium	high	term2	1.00	medium
high	medium	medium	high	term3	1.00	medium
high	medium	medium	high	term4	1.00	high
high	medium	high	low	term2	1.00	medium
high	medium	high	low	term3	1.00	medium
high	medium	high	low	term4	1.00	medium
high	medium	high	medium	term2	1.00	medium
high	medium	high	medium	term3	1.00	medium
high	medium	high	medium	term4	1.00	high
high	medium	high	high	term2	1.00	medium
high	medium	high	high	term3	1.00	high
high	medium	high	high	term4	1.00	high
high	high	low	low	term2	1.00	low

IF					THEN	
high	high	low	low	term3	1.00	low
high	high	low	low	term4	1.00	medium
high	high	low	medium	term2	1.00	low
high	high	low	medium	term3	1.00	medium
high	high	low	medium	term4	1.00	medium
high	high	low	high	term2	1.00	medium
high	high	low	high	term3	1.00	medium
high	high	low	high	term4	1.00	medium
high	high	medium	low	term2	1.00	low
high	high	medium	low	term3	1.00	medium
high	high	medium	low	term4	1.00	medium
high	high	medium	medium	term2	1.00	medium
high	high	medium	medium	term3	1.00	medium
high	high	medium	medium	term4	1.00	medium
high	high	medium	high	term2	1.00	medium
high	high	medium	high	term3	1.00	medium
high	high	medium	high	term4	1.00	medium
high	high	high	low	term2	1.00	medium
high	high	high	low	term3	1.00	medium
high	high	high	low	term4	1.00	medium
high	high	high	medium	term2	1.00	medium
high	high	high	medium	term3	1.00	medium
high	high	high	medium	term4	1.00	medium
high	high	high	high	term2	1.00	medium
high	high	high	high	term3	1.00	medium
high	high	high	high	term4	1.00	high

Table 19: Rules of the Rule Block "Efficiency"

.3 Rule Block "MacroeconomicEnvironment"

Parameter

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	BSUM
Number of Inputs:	2
Number of Outputs:	1
Number of Rules:	9

IF		THEN	
GDP	**Inflation**	**DoS**	**macroeco**
term2	term2	1.00	medium
term2	term3	1.00	low
term2	term4	1.00	low
term3	term2	1.00	high
term3	term3	1.00	medium
term3	term4	1.00	low
term4	term2	1.00	high
term4	term3	1.00	high
term4	term4	1.00	medium

Table 20: Rules of the Rule Block "MacroeconomicEnvironment"

.4 Rule Block "PrivitizationEnvironment"

Parameter

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	BSUM
Number of Inputs:	2
Number of Outputs:	1
Number of Rules:	9

IF		THEN	
AssSharForeign	**MarkCapitalizati**	**DoS**	**Privitization1**
low	low	1.00	low
low	medium	1.00	low
low	high	1.00	medium
medium	low	1.00	low
medium	medium	1.00	medium
medium	high	1.00	high
high	low	1.00	medium
high	medium	1.00	high
high	high	1.00	high

Table 21: Rules of the Rule Block "PrivitizationEnvironment"

.5 Settings

Global Options

Base Variable Data Type:	Double Precision
Computation Options:	Fast CoA

Code Generator Options

Settings:	Public Input and Output Comments
Compatibility:	ANSI C

Online Options

Communication Channel:	Serial Interface
Refresh Time:	55 ms
Timeout:	1100 ms

Appendix D

Appendix Chapter 5

D.1 Unit Root Tests Allowing for Structural Change and Dependencies between Cross Sections

It is well-known that inappropriately omitting breaks can lead to misleading inference in time series testing. It is also essential to take into account those breaks when testing the stationarity of a series.

Moreover as stated by Dobnik (2011), since the pioneering work of Perron (1988) it is well known that it is critical to allow for structural breaks when testing time series for unit roots. As Perron (1988) states "The failure to take into account the potential presence of structural breaks may lead to misleading inference regarding the order of integration. For instance, a stationary time series with a broken trend could be mistaken for a non-stationary process if the unit root test neglects the presence of structural breaks".

As stated by Chan and Pauwels (2009) although the impacts of structural instability on testing for unit root have been studied extensively for univariate time series, such impacts on panel data unit root tests are still relatively unknown. A major issue is the choice of model in accommodating different types of break (instability) prior to testing for unit root. Specifically, researchers must specify a potential break in the intercept, the trend or both before testing for unit root. Model mis-specification has been known to have a great impact on the test performance in the univariate case, especially when the selected model fails to accommodate a break in the trend. However, the impact of model mis-specification on testing for unit root is still unknown for panel data. Therefore Chan and Pauwels (2009) in their paper, tried to follow two objectives: (i) propose a new test for unit root in the presence of structural instability for panel data. The test allows the intercepts, the trend coefficients or both to change at different date for different individuals. Under some mild assumptions, the test statistics is shown to be asymptotically normal which greatly facilitates valid inferences. (ii) Using the proposed test, their paper provides a systematic study on the impact of structural instability on testing for unit root using Monte Carlo Simulation. Specifically, the impact of model mis-specification on the size and the power of the proposed test is discussed in details. Although the test performs reasonably well when the models are correctly specified, Monte Carlo results show that failure to accommodate a break in the trend coefficients can seriously distort the size and the power of the proposed test. In fact, the power of the test decreases when individuals experience a break in the trend coefficients even when the model is correctly specified. This is consistent with the results for univariate time series.

There is a large literature on stationarity tests considering structural breaks. For instance Zivot and Andrews (1992) incorporate only one break, Clemente et al. (1998) incorporates two breaks and Benati and Kapetanios (2002) incorporates even more structural breaks.

As stated by Baum (2001) a wellknown weakness of the DickeyFuller style unit root test with I(1) as a null hypothesis is, its potential confusion of structural breaks in the series as evidence of non-stationarity. Many econometricians have attempted to deal with this confusion by devising unit root tests that allow for some sort of structural instability in an otherwise deterministic model. As an illustration, consider a time series driven by a deterministic trend (perhaps subject to breaks in the mean of the series, or breaks in trend) rather than following the stochastic trend of a unit root process. One test of this nature was devised Perron (1988) who has carried out tests of the unit-root hypothesis against the alternative hypothesis of trend stationarity with a break in the trend occurring at the Great Crash of 1929 or at the 1973 oil-price shock.

After Perron in 1992 Zivot and Andrews (1992) introduce Zandrews routine in their article analysing the Great Crash of the 1930s and oil price shocks of the 1970s in terms of their effects on unitroot test behavior. This test allows for a single structural break in the intercept and/or the trend of the series, as determined by a grid search over possible breakpoints. Subsequently, the procedure conducts a DickeyFuller style unit root test conditional on the series inclusive of the estimated optimal breaks. By default, the test allows for a break in intercept. Alternatively, a trend break or both intercept and trend breaks may be considered by employing the break(string)option. One obvious weakness of the Zivot Andrews strategy, similar to tests proposed by Perron and Vogelsang (1992), is the inability to deal with more than one break in a time series. For instance, the trade weighted value of the US dollar versus trading partners currencies followed a V shaped pattern over the 1980s and 1990s, so that a single break in intercept and trend could not have dealt satisfactorily with the evolution of this series. Another drawback of this test is that it is only applicable to only single time series within panel data. This means for instance series of data for several countries over the time (this is called two dimension or one way panel). This is unlike our data series in chapter 2 where there are financial institutions in countries over the time which considered as three dimensional/two way panel or multiple panel. Therefore it implies that the test is not applicable in case of our panel data.

Hadri and Rao (2008) in his paper, extended the heterogeneous panel data stationarity test of Hadri (2000)[1] to the cases where breaks

[1] His earlier paper published in 1999 proposes a residual-based Lagrange multiplier (LM) test for a null that the individual observed series are stationary around a deterministic level or around a deterministic trend against the alternative of a unit root in panel data. The tests which are asymptotically similar under the null, belong to the locally best invariant (LBI) test statistics. The asymptotic distributions of the statistics are derived under the null and are shown to be normally distributed. Finite sample sizes and powers are considered in a Monte Carlo experiment. The empirical sizes of the tests are close to the true size even in small samples. The testing procedure is easy to apply, including, to panel data models with fixed effects, individual deterministic trends and heterogeneous errors across cross-sections. It is also shown how to apply the tests to the more general case of

are taken into account. Four models with different patterns of breaks under the null hypothesis are specified. The moments of the statistics corresponding to the four models are derived in closed form via characteristic functions. They also provide the exact moments of a modified statistic that does not asymptotically depend on the location of the break point under the null hypothesis. The cases where the break point is unknown are also considered. For the model with breaks in the level and no time trend and for the model with breaks in the level and in the time trend, they could allow for the number of breaks and their positions to differ across individuals for cases with known, unknown breaks and the modified statistic. The asymptotic distributions of all the statistics proposed are derived under the null hypothesis and are shown to be normally distributed. However finally, they have shown by simulations that their suggested tests have good performance in finite samples and balanced samples. This test also is not applicable to the case of our panel data which requires long and strongly balanced panel.

Similar to Hadri test in another recent research by Karavias and Tzavalis (2014), a new panel unit root tests are proposed for finite (fixed) T panel data models. They allow for multiple structural breaks, linear and/or nonlinear trends, spatial and temporal (serial correlation) dependence in the error terms of the dynamic panel data model. The finite T assumption of the tests make them appropriate for short panels, with small time dimensions often employed in microeconomic studies. The tests do not rely on any distributional assumptions about the initial conditions of the panel, which may be proved restrictive in practice, and they can be implemented to the case of unknown date breaks. In the last case, the paper derives the limiting distribution of the tests, analytically, based on recent results on the distribution of the minimum order statistic. This distribution is a mixture of normals and considerably facilitates calculation of the critical values of the tests (see Qian and Su (2014) and Dobnik (2011) for similar approach). This research may help us on the chapter 3 where there is short panel of 10 years. However as the test is developed newly, it meeds further programming in order to be applicable

serially correlated disturbance terms.

to real cases.

Beside Hadri test, other unit root test such as Harris-Tzavalis test and Breitung test all require strongly balanced data. In our cases the data samples are not strongly balanced. Moreover in Im-Pesaran-Shin test introduced by Im et al. (2003) and Levin-Lin-Chu test, the cross section individuals should not include data gaps. In our cases after conducting this test, z-statistics is not calculated as normality of Z-t-tilde-bar requires at least 10 observations per panel with unbalanced data.

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