Default Risk and Efficiency Nexus: Evidence from Banking Sector of Pakistan

By

ANUM ZAHRA MMS143078

MS. Scholar

A research thesis submitted to the Department of Management & Social Sciences, Capital University of Science & Technology, Islamabad in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN MANAGEMENT SCIENCES

(Finance)

DEPARTMENT OF MANAGEMENT & SOCIAL SCIENCES

Faculty of Management & Social Sciences

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY, ISLAMABAD

December, 2016

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY
ISLAMABAD

CERTIFICATE OF APPROVAL

Default Risk and Efficiency Nexus: Evidence from Banking Sector of Pakistan

by

Anum Zahra

MMS143078

THESIS EXAMINING COMMITTEE

S No	Examiner	Name	Organization
(a)	External Examiner	Dr. Attiya Ysmin Javed	PIDE, Islamabad
(b)	Internal Examiner	Mr. Ahmed Fraz	CUST, Islamabad
(c)	Supervisor	Dr. Arshad Hassan	CUST, Islamabad

Dr. Arshad Hassan
Thesis Supervisor
December, 2016

Dr. Sajid Bashir	Dr. Arshad Hassan
Head	Dean
Department of Management and Social Sciences	Faculty of Management and Social Sciences
Dated : December, 2016	Dated : December, 2016

STATEMENT BY THE CANDIDATE

This thesis includes no material which has been already accepted for the award of any other degree or diploma in any university and confirms that to the best of my knowledge the thesis includes no material previously published or written by another person, except where due reference is made in the text of the thesis.

ANUM ZAHRA

(MMS14307

CERTIFICATE

This is to certify that Ms. Anum Zahra bearing Registration No. MMS143078 has incorporated all the observations made by thesis supervisor. The title of the thesis is: **Default Risk and Efficiency Nexus: Evidence from Banking Sector of Pakistan**

Forwarded for necessary action

Dr. Arshad Hassan

(Thesis Supervisor)

Acknowledgement

All praise to Allah, the Almighty for making me able to complete this work. I am unable to thank Him for his countless blessings in my life. I would like to express my deepest gratitude to my supervisor, Respected Dr. Arshad Hassan, for his excellent guidance and supervision as well as the constant and unconditional support, which were crucial in completing this thesis. I would like to sincerely thank him for constantly believing in me and encouraging me throughout the entire MS journey. I am truly blessed to have such a great individual as my supervisor. He has also taught and trained me how to be an independent researcher. I would also like to extend my sincere gratitude to Dr. Junaid Ahmed (CUST, Islamabad), Professor Alistair Milne (University of Loughborough, UK) and Professor Md. Nurul Kabir (Griffith University, Australia) for their useful suggestions.

I would further like to thank my father, mother and mother in law, Zeenat Aunty, Uncle Ijaz, and Farhat Aunty. Thanks to them for their endless support, patience and infinite sacrifices that made it possible for me to reach this stage of my life. I want to express my heartfelt thanks to my husband, Muhammad Hassan Raza, for his moral support and faith in me which kept me going this far and finally led to completing this thesis. I am also thankful to my brothers, my sisters: Dr. Munazza Wajid, Saba Ali, Samana Qasim and Tehreem Fatima, my nieces and nephews: Hareem Fatima, Mahnoor Fatima, Mahab Fatima, Muhammad Ali Hadi, Muhammad Ali Shahmir, Rafay Ali Saleem, and Abdullah Mahdi for their unconditional love. I would further like to thank Quratul Ain Naqvi and Darrak Moin Quddusi for their love and encouragement. They always made me feel better when I was struggling with my thesis. Finally, I am thankful to all of my friends for their sincerity and kindness.

Dedication

This work is dedicated to Allah, the Almighty, who is the most merciful and the most beneficent. Furthermore, I would like to dedicate my work to the last prophet of Allah, Hazrat Muhammad SAWW, to the beloved daughter of our Holy Prophet (SAWW), Hazrat Fatima (SA), to the purified Ahulul Bait (AS) and especially to the imam of our times, Hazrat Mahdi (AS), may Allah hasten his reappearance.

List of Tables

List of Figures

List of Abbreviations

DD	Distance to Default
DEA	Data Envelopment Analysis
GMM	Generalized Method of Moments
ME	Marketability Efficiency
PE	Profitability Efficiency
E	Overall Efficiency
SFA	Stochastic Frontier Analysis
VAR	Vector Autoregressive

Abstract

The purpose of this study is to provide new evidence about the dynamic interaction between efficiency (overall, profitability and marketability efficiency) and default risk in the context of the banking sector of a developing country in South Asian region. Default risk and efficiency nexus is one of the highly controversial topics in the literature. The study uses a panel data set of 22 banks of Pakistan from 2004 to 2014. The procedure of the study is comprised of three phases. First, overall, profitability and marketability efficiency scores are estimated using two types of two-stage DEA models. Then default risk is measured using KMV Merton model. In the last step, panel VAR is applied to examine the underlying relationship between overall, profitability and marketability efficiency of banks and their default risk because panel VAR technique can be implemented without a-priori restrictions. Results indicate that default risk and efficiency are interrelated and they exhibit complex interdependencies. These findings are useful for regulators in formulating measures to ensure the stability of banking sector that will, in turn, lead to economic growth.

Key Words: *Default risk, efficiency, marketability efficiency, profitability efficiency, Pakistan*

Table of Contents

CHAPTER 1

INTRODUCTION

Financial institutions lay at the heart of every economy. Inefficient banking systems then may have severe implications for the overall economic performance and may eventually lead to a crisis. Recent financial crisis, the most important economic event after 1930, shed light on the important role of banks in the financial system. Financial turmoil is aggravated by the defaults in the banking sector which in turn lead towards the instability of the economic system. The phenomenon of increased default tendencies during financial crisis showed miss assessment of risk by the banks, their supervisors as well as by the investors of banks. Assessment of risk has become challenging in today's fast paced world due to increased uncertainties and their accompanying risks. The changes that are taking place in the financial environment of the world in the form of increased competition, integration, consolidation, globalisation, financial liberalisation, as well as continuous innovations, are the major cause of increasing uncertainties and risks for financial institutions especially for the banks. Thus, risk management has become more challenging than in the past. Management of risks and safeguarding banks' stability is important because the financial instability of banks has far-reaching consequences for the financial as well as the economic system. Default risk is widely used as a measure of banking stability. Default risk of banks can be defined as the probability of default to fulfilling financial obligations on time or at all, by the banks. A banking firm defaults when it falls short of the resources required to fulfil its financial commitments. When banks default then not only their shareholders, deposit guarantee schemes and clients suffer financially, but the default of banks also cause loss of competition and destabilisation of the overall financial system due to contagion mechanism which in turn leads to a banking crisis. The default of banks results in disturbance of credit flow, money supply reduction and the loss of real economy.

Minsky (1992) states that efficient working of financial institutions ultimately leads to macroeconomic stability through the optimum allocation of financial resources that spur macroeconomic growth. The efficiency of a bank measures how inputs to the banking operation can be minimised to produce a certain amount of outputs or how to use a certain amount of inputs to maximise output production. This reflects management's skills in managing inputs and outputs, appropriately. Druker (1963) states that a measure of efficiency appraises the organisation's ability to achieve the output(s) considering the minimum inputs level. Luo (2003) report that management quality i.e. profitability efficiency is a major determinant of a commercial bank's failure. However, the efficiency of a bank is not solely based upon the quality of its management. Other than profitability efficiency, marketability efficiency is also a vital indicator of a commercial bank's efficiency level because the real value of a commercial bank is defined by its performance in the stock market. Therefore, the overall efficiency of a commercial bank needs to be decomposed into profitability efficiency and marketability efficiency to better identify the source of inefficiency.

Efficiency is regarded as a key indicator for evaluating a banking firm's performance. Banking firms perform various profit seeking and value increasing activities which involve different types and levels of risk. Efficiency in resource allocation and performance of business activities is considered almost essential for the profitable functioning of firms to improve financial health and ultimately the firm value. Efficiency-stability hypothesis argues that efficient banks have better screening and monitoring mechanisms for the borrowers, helping to lower the default probability of the banks. Furthermore, efficient allocation of resources also helps to increase the stability of banks. Inefficient banking firms are considered a constant threat to the financial stability because these banks are prone to failure resulting in weakening of the banking sector at large (Bank for International Settlements, 2002). Some authors investigated the relationship between efficiency and bank failure, for example, Wheelock and Wilson, (1995) report that banks experiencing financial distress are located far from the efficiency frontier.

On the other hand, efficiency improvements may come at the expense of deteriorating bank profits and excessive risk-taking. A primary proposition of welfare economics necessitates perfect competition for the efficient performance of the banking firms. Increase in competition to enhance efficiency leads to a decrease in prices which become close to marginal costs resulting in declining profitability levels and ultimately forcing the banks out of the financial markets. On the other hand, banking firms on the edge of exit face a constant pressure to improve efficiency which induce them to indulge in highly risky activities in order to gamble for their revival (Amel, Barnes, Panetta, & Salleo, 2004).

It has been argued that bank failures are related to the output (such as profit) performance of the banks. It has also been noted that management driven weaknesses (profitability inefficiency) play a significant part in determining bank failures. However, some authors argue that efficiency and stability level are the mutually exclusive phenomenon. Similarly, it could be expected that marketability efficiency plays a role regarding the impact of first-come, first-served rule and information externalities on bank failure contagion effect. Also, it can be expected that banks with higher marketability efficiency may be less influenced by such contagion effect, but Luo (2003) report that marketability efficiency does not contribute towards the determination of banking failure. Given the lack of consensus about the relationship between a bank's efficiency and stability level, the present study explores the association of default risk with banking marketability, profitability and overall efficiency level. To account for the unique features of a financial sector of a developing nation of South Asia where both the Islamic and conventional banks co-exit, the study is conducted in the context of the banking sector of Pakistan.

1.1. Theoretical Background

To find the causal link between default risk and efficiency, Berger and Deyoung (1997) developed four hypotheses which were further elaborated by Hughes (1999), Koutsomanoli-Filippaki and Mamatzakis (2009) and Saeed and Izzeldin (2014). These are not mutually exclusive. Any of the hypothesis can be more relevant in describing the causal link between default risk and efficiency of Pakistani banks. Hypotheses are outlined from the default risk perspective because it is more interesting from the policy making a point of view.

The first one is bad luck hypothesis which postulates that an increase in default risk of a bank leads to a decline in efficiency level of that bank. This hypothesis implies a negative relationship between risk and efficiency. The hypothesis suggests that a rise in a banking firm's risk level which transforms into its likelihood of default will make management less efficient in performing business activities. The reason for this phenomenon is extra precautionary expenses and other costs being incurred to monitor rising risk level, in order to maintain the portfolio quality of the banking firm, which is facing soaring risks. Managers will not be able to exert full energy in solving the daily operational issues and following efficiency enhancing tactics in order to prevent further financial distress situation. Moreover, if the extreme situation is considered when a banking firm is at the brink of failure, either near or below the default threshold level, the banking firm will have to bear tremendous costs to defend its safety level and financial soundness record in front of the market players and towards its supervisors. In both of the scenarios, a rise in costs due to increased default risk will result in decreased efficiency level.

The efficient market hypothesis proposed by Fama (1965) can also explain the negative relationship between risk and efficiency. Given the fact that developments in the stock exchange and stock prices influence risk measure because prices reflect future information. Thus, any form of an event such as credit or liquidity crises impact the share prices of a banking firm which will result in increased default likelihood. Increased default risk will affect the values of the variables to estimate efficiency because inputs and outputs are derived from balance-sheet data which shows developments with an annual lag. Therefore, the direction of causality will be from risk to efficiency in the setting of an efficient stock market.

The second hypothesis is bad management hypothesis, which argues that decrease in efficiency level causes an increase in default risk. According to this hypothesis, poor management strategies result in a decline in efficiency level. The management of a banking firm may not be able to properly manage the performance of usual business activities and monitoring of risk. Cost and profit inefficiency signal rising operating expenses and declining profits due to poor management. Thus, it is reasonable to assume that risk is being managed inappropriately. For instance, proper capital budgeting techniques are not followed in selecting projects and bad managers can forward poor quality loans. Therefore, reduced efficiency due to bad management practices lead to inappropriate management of risks which result in rising risk levels. The increase in risks result in unexpected losses which effect the financial health in a bad way. In other words, a decrease in efficiency leads to high default risk.

Third is skimping hypothesis which suggests that an increase in efficiency results in increased default risk of a bank. According to the moral hazard hypothesis proposed by Gorton and Rosen (1995), senior managers of an efficient banking firm can exercise their power to pursue an expansionary strategy which is beneficial to the managers instead of the owners in a sense that it gives benefits in the short run, but in the long run it results in increased risk level for the bank. However, the financial distress situation may be revealed after a lapse of time because most of the contracts of a banking firm are based on the promise of future payment. Thus, according to the skimping hypothesis, a banking firm may have a high level of efficiency by skipping over loan monitoring costs, cutting necessary operating costs, or by entering into bad loan contracts, resulting in high chances of default.

The fourth is risk averse management hypothesis which postulates that a decrease in the efficiency level will lead to decreased default risk of a bank. Ceteris paribus, a decrease in efficiency in the short term could result in decreased participation in risk taking actions which ultimately lead towards a decrease in the default risk with a lag. Thus, it could be implied that risk averse management strategies are being practiced by the management of the banks which result in a rise in operating expenses and a decrease in efficiency in the short term period, resulting in a reduction in default risk. It has been reported by Hull (1999) that uncertainty regarding a probable occurrence of a costly financial distress situation or asymmetry of information can induce managers of the banks to practice risk averse management. Thus, this hypothesis is usually termed as the 'risk-averse management' hypothesis.

1.2. Research Gap

Since the last two decades, several authors tried to link efficiency and default risk of financial institutions. Some researchers treated efficiency as an explanatory variable in financial distress prediction models in order to evaluate financial soundness status of banking firms (Barr & Siems, 1994). Another group of researchers incorporated various aspects of risk in the efficient frontier (Pastor & Serrano, 2005). Others applied a two stage approach to examine the link between efficiency and risk, where inefficiency is regressed on a set of variables capturing risk

(Yildirim & Philippatos, 2007). However, results are inconclusive and limited at the theoretical level. Similarly, only a few studies provided a comprehensive empirical evidence of the causal link between default risk and efficiency. For example, Koetter and Porath (2007) found that efficiency improvements bring an increase in profits and reduction in risk and the effect of efficiency improvements is persistent on profit and risk. Similarly, Koutsomanoli-Filippaki and Mamatzakis (2009) report a positive relationship between efficiency and the distance to default. Whereas, the direction of causality was from default risk to efficiency. Saeed and Izzeldin (2014) stated that efficiency and risk show complex interrelations in both Islamic as well as in conventional banks. Their study has varying results for efficiency and default risk interrelations in conventional and Islamic banks. They report a tradeoff between bank efficiency and default risk in conventional banks while this trade off was absent in Islamic banks. However, most of the studies which analyse the dynamic interrelations between efficiency and default risk using a panel VAR approach applied a parametric approach to measure efficiency and ignored the marketability aspect of efficiency as well. Therefore a gap exist in the literature to analyse the causal relationship between default risk and efficiency by using efficiency derived from a non-parametric approach. Similarly, other than the interaction between profitability efficiency and default risk, the empirical evidence about the causal relationship between a bank's standing in the stock market (marketability efficiency) and its default risk level is also scarce in the literature.

1.3. Problem Statement

The increase in default likelihood of banks during last decade differs between banking systems and across regions. For example, default tendencies of US and European banks were higher as compared to Australian banks. The number of distressed banks in the U.S. has declined after

2010; this has not been the case in Europe where banks in many countries are still facing extreme pressures. Whereas most of the Asian banks stayed resilient during last decade, and default tendencies were low in Asia. However, the banking systems of Asian countries show different results. This phenomenon implied that each country has some unique features in the banking system due to some macroeconomic factors.

Efficiency is also considered an important performance parameter. Efficiency stability hypothesis argues that efficient performance of banks is a significant contributor towards ensuring stability level. However, there is a lack of consensus among researchers about the existence of a causal relationship between efficiency and default risk.

Similarly, the nature of the causal link between efficiency and default risk of banks can differ across banking system of different countries. Pakistan enjoys a strategic position as a developing country of South Asia. Pakistani banking sector is considered as the most integral part of its financial system. Therefore, research about the causal interrelationship between default risk and efficiency in a single country context with a time span involving a pre and post-crisis period is needed to provide the convincing argument about the causal relationship between efficiency and default risk.

1.4. Research Questions

Whether there exist a causal relationship between efficiency and default risk of banks?

Whether there exist a relationship between overall efficiency and default risk of banks?

Is there any inter-relatedness between profitability efficiency and default risk of banks?

Is there any relationship between marketability efficiency and default risk of banks?

1.5. Research Objective

To underpin intricate Interrelations between default risk and efficiency level of banking firms

1.6. Significance of the Study

The present study is contributing towards the existing literature about default risk and efficiency nexus in several ways. First, the study provides useful insights about the intricate interrelations between efficiency and default risk by decomposing efficiency into profitability and marketability components. Efficiency is measured by using a popular non-parametric approach, data envelopment analysis (DEA). An advanced model proposed by Kao and Hwang (2008) for the decomposition of efficiency into two stages is used. The model accounts for the serial relationship between two stages. For the sake of robustness of efficiency scores, another older but widely used model developed by Seiford and Zhu (1999) is also used to measure efficiency scores. To calculate efficiency scores, negative values of efficiency variables are usually omitted in most of the DEA studies which result in the decline in some observations. However, the present study takes into account the negative values of input and output variables of efficiency and uses a recently developed technique to deal with the negative data. The study account for the endogenous nature of variables and applies panel VAR approach by using a recent package of programs developed by Abrigo and Love (2015) to apply panel VAR. Default risk is measured by using a more comprehensive technique, KMV Merton model instead of traditional ratio analysis. Finally, the causal relationship between efficiency and default risk is analysed by applying panel VAR approach between efficiency scores obtained from independent model and the distance to default, additionally, panel VAR is used between efficiency score obtained from relational model and distance to default. Afterwards, the results are compared for the sake of robustness. The present study also provides useful insights about efficiency and default risk nexus in the context of the banking system of Pakistan. According to the finest knowledge of the author, this is the first study analysing the complicated causal relationship between default risk and efficiency within a single country context of South Asia.

1.7. Plan of the Study

The study is organised as follows: First chapter comprises of introductory text regarding default risk and efficiency of banks followed by theoretical background, research gap, problem statement, research questions, research objectives and significance of the study. The second chapter provides an overview of the existing literature regarding default risk and efficiency and states proposed hypothesis. The third chapter provides information regarding data and methodology used in the study. Results and their interpretation are stated in the fourth chapter. Finally, the fifth chapter contains conclusion, policy recommendations, limitations and future research directions.

CHAPTER 2

LITERATURE REVIEW

Stability and efficiency have remained the widest research strands for financial institutions since past several years. However, quite a few studies tried to analyse the intersection between these two strands of research.

Banking stability has become the center of attention of many researchers upon observing the disastrous consequences of defaults in the banking sector on an economy that became evident in the recent financial crisis (Agnello and Sousa, 2011). Therefore, many academics have examined the factors that trigger a crisis in the banking sector. Credit risk is the most important risk for banks because it is mainly responsible for the instability of banks. A primary function of banks is to act as intermediaries between investors (depositors) and borrowers. Thus, a major part of bank revenue is dependent upon advances and loans. In this context, exploration of factors that give rise to credit problems is critical in order to maintain financial stability. Given the fact that banking crisis can occur as a result of adverse changes in macroeconomic environment or worsening of banks specific conditions. The literature generally classifies the determinants of credit risk into two categories: the first category of studies explore macroeconomic factors which affect systematic credit risk of banks, while the second category of studies is related to the analysis of bank-specific factors which affect unsystematic credit risk of banks.

Some studies use both kinds of determinants of credit risk. For example, Chaibi and Ftiti (2015) analysed that whether the effect of bank-specific and macroeconomic factors on loan quality varies in a market based (France) and bank based (Germany) economy. They examined non-performing loans' determinants of French and German banks from 2005 to 2011 by applying dynamic panel data approach. They observed a significant effect of GDP growth, exchange rate, the rate of unemployment and interest rate on loan quality in both countries. However, the inflation rate was significant in market-based economy only. Bank size and profitability from bank-specific factors showed a strong effect in both economies. They observed that credit risk is high in market-based economy (i.e. France) because inefficiency and loan loss provisions were significant determinants of credit risk in market-based economy only while leverage was significant in Germany. Similarly, Louzis, Vouldis and Metaxas (2012) also explored effect of both bank-specific and macroeconomic factors on non-performing loans by applying dynamic panel data approaches. They considered consumer and business loans as well as mortgages of Greek banks from 2003 to 2009. They find that macroeconomic variables (public debt, unemployment rate, real GDP growth rate and interest rate) are significant determinants of credit risk. Moreover, bank performance and efficiency indicators, from bank-specific variables also determine credit risk of Greek banks.

Studies that examined the effect of macro-economic determinants of credit risk include work by Festic, Kavkler and Repina (2011). Their study assessed the vulnerability of banks to non-performing loans at the macroeconomic level. They analysed banking sectors of five recent additions to European Union member countries: Romania, Latvia, Lithuania and Estonia from

1995 to 2009. They find that the lack of supervision, slowdown in economic activity, and growth of credit and finance availability results in decreasing NPL dynamics. Similarly, in the European context, the relationship between credit risk and macroeconomic developments is studied by Castro (2013) in Greece, Portugal, Italy, Ireland and Spain (PIIGS). The results of the study showed that the recent financial crisis, housing price indices, credit growth, GPD growth, unemployment rates, real exchange rates and interest rates significantly affect credit risk.

Researchers that analysed the effect of bank-specific determinants of credit risk include Berger and DeYoung (1997) and Podpiera and Weill (2008), to name a few. Ahmad and Ariff (2007) also analysed the link between bank-specific factors and credit risk. They compared bank-specific determinants in the banking systems of developed and emerging economies. They find that management quality plays a vital role in loan dominated banking firms of developing countries and they emphasised the importance of regulatory capital for banks offering extensive product range.

Given the importance of default risk of financial institutions, several researchers reviewed the methods used to measure default risk of banks. Kabir, Worthington and Gupta (2015) stated that the measure chosen plays a significant role in assessing the actual credit risk of banks. Merton's distance to default has been regarded so far the most widely used method for assessing default risk. The practicality of Merton's model in computing DD, to estimate the financial stability of banking firms, has been reviewed by many researchers. For example, Chan-Lau, Jobert and Kong (2004) conducted a study in context of an emerging world and estimated distance to default of thirty eight banks of fourteen countries. The authors report that distance to default can predict decline in credit ratings up to nine months ahead of time. In the European context, distance to default is estimated by Gropp, Vesala and Vulpes (2004) in order to evaluate the financial health condition of the banks. The authors confirm the efficiency of Merton model in predicting financial distress up to 12 to 18 months in advance. The authors also report that the measure is free from biases. In sum, distance to default is considered a very useful technique to analyse financial stability. It has become a part of the Global Financial Stability Report of the International Monitory Fund. Similarly, it is being used in the Financial Stability Review by the European Central Bank. Jessen and Lando (2015) test the robustness of distance to default. Simulations are used to prove that distance to default is strongly robust to model misspecifications which is the reason of its empirical popularity. The authors considered many deviations from the Merton model. The deviations include different asset value dynamics and different default triggering tools. The authors report that distance to default has successfully ranked default probabilities of the firms, despite altering primary assumptions of the Merton's model. They concluded that DD is a strong predictor of default.

Another group of researchers worked on proposing models for prediction of bank distress and found that profitability is an important indicator of financial soundness. Cleary and Hebb (2016) examined the failure of banking firms in America from 2002 to 2009. They proposed a model based on multivariate discriminant analysis for prediction of financial distress in banking firms by employing a sample of 132 failed American banks with matched pair of successful banks. The authors placed emphasis on loan quality and capital in order to assess the financial health of banks. However, the authors did not negate the importance of profitability as an important indicator for predicting financial distress. The resulting predictive accuracy of 92% proved that their model is functional and efficient. The model's out of sample predictive accuracy was also 90-95% when it was employed (out of sample) on 191 banks for 2010-2011to examine failure.

Efficiency is one of the most important performance parameters. Therefore, the efficiency of banking institutions is regarded as a critical research stream. Olson and Zoubi (2011) classify bank performance studies into two categories which are accounting based studies and economic based studies. Accounting based studies use information from the financial statements while economic based studies employ Distribution free approaches, Data envelopment analysis or Stochastic Frontier Analysis. Some studies for example Yildirim and Philipatos (2007) combine both approaches and found that difference in cost and profit efficiency scores was 9 to 59% when only accounting based techniques were used.

Kumar (2016) conducted an accounting based study to analyse performance and stability of ten UAE national commercial banks in the crisis and post financial crisis period (2008-2013). The author used return on assets and return on equity to measure banks' performance while CAMEL parameters and Z score were used to measure banks' stability. Results showed that performance of banks declined in the crisis period from 2008 to 2010 and improved afterwards. However, UAE banks showed stability which can be attributed to stable political condition, economic policies and good governance.

Since a good performance is concerned with high efficiency and effectiveness, much effort has been devoted over the past decades among researchers to estimate the level of efficiency with which banks work in comparison to their competitors. The literature of the bank efficiency measurement can be classified into different categories based on the method of analysis. Regarding the method of analysis, there are numerous techniques used to measure bank operational efficiency such as ratios (Heizer and Render, 2006) and regression analysis (Hensel, 2003). However, those traditional techniques have become unsatisfactory analysis methods due to some limitations. In recent years, two competing frontier efficiency approaches – the SFA and

DEA – have been proposed as alternative techniques for measuring the relative efficiency of any financial institution against the group's observed best practice. The popularity of DEA in measuring the relative efficiency is due to several distinguishing features that make them a valuable and attractive tool for performance analysis. Ruggiero (2007) shows that the SFA model does not produce better results than DEA. Therefore, a large number of authors used DEA to measure banking efficiency (for example Luo, 2003; Mostafa, 2007; Tahir, Abu Bakar & Haron, 2009; Chiu, Chen & Bai, 2011; Chen, Chiu, Jan, Chen & Lu, 2015)

Some studies theorise upon the relationship between competition and stability by taking the implicit assumption that competition enhances efficiency. Two dominant hypotheses are available in the banking literature with regards to relationships between competition and stability. These hypotheses are often referred to as the competition–fragility hypotheses and the competition–stability hypotheses. The former argues that market power (as opposed to competition) increases stability, since banks with greater market power have the ability to reduce the asymmetric information problem, and have higher quality screening and monitoring methods to select creditworthy borrowers, as well as the ability to charge higher interest rates (Petersen & Rajan, 1995). Ariss (2010) argues that excessive competition can erode the franchise value of banks leading to financial fragility.

However, this conventional idea is challenged by recent studies which conclude that competition increases stability, since more competition helps banks to be more innovative and more efficient and eventually increases their stability (Boyd and De Nicolo, 2005; Dima, Dinca & Spulbar, 2014; Nicoló, De Nicol, Jalal & Boyd, 2006). Competition can also enhance bank stability through bringing about efficiency, promoting new product innovation and enhancing loan portfolio diversification (Fiordelisi & Mare, 2014). Both views enjoy the theoretical and empirical support and hence no conclusive findings are available to date.

Existing competition–stability theories indicate that ‘efficiency’ could be one of the transmission mechanisms through which competition affects stability (Dima et al., 2014). It can be argued that if competition increases, and to survive in the more competitive market banks will diversify, introducing new and innovative products and services and reducing their cost resulting in efficiency increase. Thus, efficiency can positively affect stability (Schaeck & Cihák, 2014; Nurul & Worthington, 2015).Chen (2007) found that improved competitive pressure results in more efficient screening and monitoring of borrowers which leads to better performance by borrower. Schaeck and Cihák (2014) analysed transmission mechanism of banking stability and competition. They used data from banks of Belgium, Denmark, Austria, England, Germany, Luxembourg, ,France, Italy, Netherland and Switzerland from 1995 to 2005. Z score was used to measure stability while Boone (2008) indicator was used as competition proxy. They identify that competition affects stability through efficiency. Without explicitly measuring efficiency, here they argue that the Boone indicator is a function of efficiency, thus a negative relationship between the Boone indicator (the higher the Boone indicator, the lower the competition) and the Z-score would indicate that competition increases stability through the efficiency mechanism.

Another study that investigates the transmission mechanism of competition and stability is by Dima et al. (2014). Using macro-economic data from 63 developed and developing economies from 1997 to 2010, they conclude that large and efficient banks are able to benefit from sector concentration and capital market development. They use the Lerner index as a measure of competition and the Z-score as a measure of stability to test the relationship between competition and stability. The study aimed to analyse the financial nexus formed by the banks' soundness, concentration and efficiency in the banking sector and the development of the capital markets. The relation between soundness, structural and functional characteristics of the sector is significantly influenced by the banks' performances.

Similarly, Nurul and Worthington (2015) investigated about the appropriateness of ‘efficiency’ as a channel through which competition affects stability in the Islamic and conventional banking sectors. The authors employed three dominant hypotheses in the banking literature to establish this relationship: the ‘competition–efficiency’ hypothesis, the ‘efficiency–stability’ hypothesis and the ‘competition–stability’ hypothesis. The dataset comprised 324 banks from 13 countries for the years 2000 to 2012 where both banking systems coexisted. The findings suggested that although efficiency had a significant impact on stability in conventional banks; it did not have any significant impact on Islamic banks. Thus, the results cast doubt on the findings of whether ‘efficiency’ is an appropriate channel to significantly modulate the linkage between competition and stability.

Given the fact that risk management and correct risk pricing is crucial for banks to effectively manage their performance, some authors accounted for risk management perspective while measuring and comparing efficiency scores of banks.

Eken and Kale (2013) benchmarked risk efficiency of twenty banks in Turkey using four slack based models of DEA. The authors used risks as inputs and profit as output, where inputs are selected to be risks and outputs are profitability. The first model, which is net interest margin model (NIM), gaining maximum net interest margin is dependent upon efficient management of interest rate, liquidity, foreign exchange and credit risk . Efficient management of financial as well as operational risks in order to obtain maximum ROA is analysed under ROAA model. The successful conversion of all of the risks into return on equity has been analysed in ROAE model. Measurement of bank effectiveness in risk maintenance at some specified level while maximising outputs at the same time is analysed under ALL model. Their results showed that risk-taking preferences are not parallel with banks' profitability. Comparison of risk efficiency of banks can determine that either the bank's profitability is reasonable as compared to the risk levels or not. The results implied that banks should manage risk efficiency either by increasing profitability or by reducing risks. In the long term, low profitability leads to reduced market share and financial instability.

Sometimes a bank with high credit risk can be considered as more efficient than a bank with low credit risk because the former is skimping on credit evaluations or producing risky loans than the latter while the latter is using its resources for credit evaluations. In order to examine credit risk impact on efficiency, Pasiouras (2008) used loan loss provisions as input to measure efficiency scores of Greek banks. The author employed DEA to measure efficiency from 2000 to 2004.Their results showed that accounting for loan loss provision increased efficiency scores. According to their results, Loan activity, as well as capitalization and market power increased the efficiency of banks.

Banks should be monitored for credit risk because credit risk impact profitability of banks and profitability is an important predictor of bank's financial stability. Funso, Kolade, and Ojo (2012) investigated the impact of credit risk on banking profitability. They used a panel of five Nigerian commercial banks from 2000 to 2010. The results of their study showed that increase in non-performing loans and loan loss provisions decrease profitability (measured by return on assets). Whereas an increase in advances and loans cause profitability of banks to rise, since interest bearing loans constitute a significant part of a banks' revenue.

A number of studies proved that contagion effect exists in banking sector For example Aharony and Swary (1996) found evidence of Contagion effect in Southwestern banks. After the global financial crisis, several studies analysed the factors that link banking system performance to the stability of financial system at the country level and cross-country level. However, literature is scarce on the causal link between efficiency and risk of banks despite a surge of interest to study the relationship between the aforementioned two variables of the banking sector. Wheelock and Wilson (2000) found an association between default risk and banking inefficiency and stated that banking inefficiency increases failure risk. They examined determinant factors of failures in US banking sector from 1984 to 1993. They estimated hazard models of competing risks with time-dependent covariates based on information derived from bank-specific factors similar to that used in CAMELS rating system (i.e. "CAMELS stands for capital adequacy, asset quality, management, earnings, liquidity and sensitivity"). The authors found that decrease in alternative x efficiency measures, which are reflections of management quality, results in increased default risk and reduced probability of bank acquisition. They also found that banks which are nearer to insolvency have more chances of possible acquisitions. They further stated that cost inefficient and technically inefficient banks have more chances of failure while they are less likely to be acquired because inefficiency makes banks an unattractive target for acquisitions due to inefficiency associated high costs.

Furthermore, the seminal work by Berger and Deyoung (1997) provided empirical evidence regarding the relationship between efficiency and credit risk in the context of US banking industry. The authors tested the four competing as well as complementary hypotheses regarding intertemporal relations between cost efficiency, non-performing loans and financial capital. They employed granger-causality techniques to test bad luck, bad management and skimping hypotheses for intertemporal relations between cost efficiency and loan quality as well as moral hazard hypothesis was tested to underpin intertemporal relationships between financial capital and loan quality. They used data of commercial banks from 1985 to 1994. Results suggested that loan quality and cost efficiency have a bi-directional intertemporal relationship. They found evidence to support bad luck hypothesis for the data. The entire industry data supported bad management hypothesis. The skimping hypothesis was proved only for the subset of efficient banks in the data whereas the subset of banks with low capital ratios supported moral hazard hypothesis.

Williams (2004) test the robustness of the study conducted by Berger and DeYoung (1997). The data set of saving banks of Europe for a period of eight years (1990-1998) is employed. The author use the ratio of loan loss provisions to total loans as a proxy for the quality of loans. Stochastic frontier analysis was used to measure the cost and profit efficiency. The author found evidence of bad management hypothesis of Berger and DeYoung (1997) because the direction of causality was from efficiency to risk. The study of William (2004) was further extended by Rossi, Schwaiger, and Winkler (2005). The context of the study was economies in the phase of transition. The sample comprised of 278 banking firms from 9 economies for a period of 1995-2002. The purpose of the study was aligned with the former studies that is to find an association between loan quality, efficiency and capitalization of the banks. The methodology was in line with the study of William (2004). The authors report evidence of bad luck hypothesis because the direction of causality was found to be from risk to efficiency.

Furthermore, the work of Berger and Deyoung (1997) was also extended by Podpiera and Weill (2008). They examined the causality between NPLs (non-performing loans) and cost efficiency in order to identify the determinants of bank defaults. They extended the work of Berger and

DeYoung (1997) by using GMM dynamic panel estimation techniques instead of granger causality model alone to predict causal links between variables mentioned above. Moreover, they employed DFA to measure cost efficiency scores while Berger and DeYoung (1997) used Econometric Frontier Approach (EFA) to take short-term estimates of cost efficiency. Their dataset comprised of a panel of 43 banks of Czech Republic from 1994-2005. According to their results cost inefficiency precedes NPLs increase; they supported bad management hypothesis and rejected bad luck hypothesis whereas Berger and DeYoung (1997) supported bad luck hypothesis. Their findings hold for compensated and uncompensated NPLs (non-performing loans).

Some other studies focus on the relationship between banking efficiency and default risk of banks. For example, Reynaud (2010) tested efficiency analysis efficacy for banking failure predictions in the context of Turkey. They used banking crisis of Turkey in the year 2001 as a case study. The efficiency scores for fifty five Turkish banks were estimated. In the first stage, the authors used both parametric and non parametric approach SFA and DEA to estimate efficiency from 1996 to 2001. These scores are tested against the standard CAMELS ("CAMELS stand for capital adequacy, asset quality, management, earning, liquidity and sensitivity") model to analyze their capability to predict banks' default likelihood. The results show that failed banks had low cost efficiency scores as compared to their counterparts. Similarly, Podpiera and Podpiera (2005) also showed that cost inefficiency could be a plausible signal of failure risk for a bank. They used three measure to calculate efficiency scores (Stochastic frontier analysis, REM, and FEM)and observed Czech banking sector comprised of 19 banks in its transformation period from 1994 to 2002. The authors concluded that cost inefficient management and default risk of banks was closely related. They observed that failed banks were placed in the least efficient quartile of relative efficiency ranking before one year of their failure. Furthermore, they found that monetary policy rates had an indirect impact on bank failures by influencing efficiency scores.

Fiordelisi, Marques-Ibanez, and Molyneux (2011) analysed the dynamic relations of bank performance and credit risk in response to changes in efficiency level in the European context. Their sample consisted of British, Spanish, German, Italian and Frensch bank. The data period used in their study was from 1995 to 2007. They used granger causality method for panel data to test four hypothesis developed by Berger and DeYoung (1997). They employed SFA to measure scores cost and revenue efficiency while the risk was measured by Moody's KMV model and traditional non-performing to total loans approach. Capital adequacy was measured by total equity to total asset ratio. They concluded that decrease in revenue and cost efficiency increases failure risk and improvements in cost efficiency are preceded by a capital increase. The authors found support for bad management hypothesis and they also suggested that the efficient banks become better capitalised that eventually effect efficiency in a positive way. The importance of attaining long-term efficiency improvements to achieve financial stability objective is underlined by the results of their study.

Koetter and Porath (2007) were the first to apply panel VAR approach to analyse the dynamic relationship between performance and efficiency in German banking sector by using a panel VAR approach. To measure performance, they assessed profitability and default risk level of banks. Return on asset proxy was used for profitability while default risk was estimated using hazard rate model. Cost and profit efficiency scores were obtained using SFA. They used panel data of banks for 1993-2004.They calculated Impulse response function derived from VAR model to analyse the relationship. The study found that efficiency improvements bring improvement in performance by increasing profits and reducing default risk. The results suggested that, in the short run, default risk is reduced by rising cost efficiency whereas, in the long term, profit efficiency needs to be increased to reduce default risk of banks.

Koutsomanoli-Filippaki and Mamatzakis (2009) applied panel VAR approach to study the causal link between efficiency and default risk of the banking sector. They used data of banks situated in 27 countries which are European Union members for the period of 1998 to 2006. They estimated three efficiency measures which are: cost profit and productive efficiency. They employed a parametric technique i.e. Stochastic frontier analysis to assess productive efficiency under directional distance function. The stochastic frontier approach was used to estimate the other two efficiency measures (cost and profit efficiency). The authors used distance to default as a proxy for banks' default risk. Panel VAR was applied comprehensively to study the underlying dynamic relationships of efficiency and risk. They have also performed a sensitivity analysis to examine whether the relationship between probability of default and efficiency varies across different ownership structures of banks and varying levels of financial development of financial systems. The findings of this study showed that trade-off between efficiency and default risk might not exist. The results of Impulse Response Function and Variance Decomposition revealed that overall causality runs from the risk of default to inefficiency. The study provided evidence of a negative relationship between them. The direction of the causal link from inefficiency towards default risk is not negated, but it is weak. Sensitivity analysis showed that in the case of domestic as well as foreign banks, causality ran from cost inefficiency to risk. Same was the case with profit inefficiency in sub-samples of the countries with less financial development and domestic banks. Moreover, the effect of default probability on productive inefficiency was positive in low financially developed countries.

Tabak, Craveiro and Cajueiro (2011) conducted a study for the identification of relevant factors that can anticipate bank failures and ultimately that can act as first harbingers of systematic instability. They analysed the relationship between bank efficiency and non-performing loans. They used DEA to estimate scores of economic, allocative and technical efficiency. A panel VAR approach accompanied by a dynamic panel approach is used. Semiannual data of Brazilian banks from June-2000 to June-2007 was used. Their results indicated that inefficiency triggers rise in problem loans. Thus, efficiency measures can serve as critical early warning signs of instability.

Another group of researchers compared default risk and efficiency nexus of Islamic and conventional bank. Saeed and Izzeldin (2014) applied a panel VAR technique to find the causal link between default risk and efficiency in a comparative setup of Islamic and conventional banks of eight countries (five GCC and three non GCC). Their observed period was from 2002-2010. They used Stochastic Frontier Analysis to measure cost and profit efficiency while default risk was measured using Merton's distance to default approach. The authors concluded that default risk and efficiency are interdependent in a complex way. They observed variations in profit efficiency and default risk relationship across their sample. Default risk decrease has an association with efficiency decrease in Conventional banks and for banks in GCC region. Causality from profit efficiency to default probability is inverse. The study found the existence of a trade-off between default likelihood and efficiency in conventional banks, whereas the trade-off was not present in the case of their Islamic counterparts. This finding is a sign of Islamic banks' instability.

Although the causal link between profitability efficiency and default risk has been investigated by a few researchers, there is a scarcity of literature linking marketability efficiency and probability of default. Attaining marketability efficiency is crucial for banks because the current share price of bank is a true reflection of the real value of the bank. Therefore, efficient performance of market value increasing activities has equal importance like profit generating activities. Some authors analysed the marketability efficiency of banks. These studies used two-stage DEA model to compute profitability and marketability efficiency and considered internal structure of the decision-making units (banks). Castelli, Pesenti, and Ukovich (2010) provided an excellent review of studies that contributed to DEA literature which considers internal structure of decision-making units. Seiford and Zhu (1999) divide a commercial bank's production process into the stages of profitability and marketability. The efficiencies of the first stage, second stage, and the whole production process are calculated via three independent DEA models for 55 US commercial banks. The authors argue that the decomposition of the production process helped identify the source of inefficiency. Shahwan and Hassan (2013) explored the usefulness of DEA to evaluate the relative efficiency of UAE banks using three different dimensions (profitability, marketability, and social disclosure). The primary findings implied that the majority of Emirati banks obtain high level of profitability and social disclosure efficiency while UAE banks were found to be inefficient regarding marketability activities. Luo (2003) evaluated the efficiency of 245 large banks of US, for the year 2000, from profitability and marketability perspective. The author investigated whether profitability and marketability efficiency can help in the prediction of a large bank's default alongside investigating differences in profitability and marketability efficiency levels of large banks as well as the impact of bank location on efficiency level of large banks is also investigated. The author used Data Envelopment Analysis (a non-parametric approach) to find scores of marketability and profitability efficiency. Production approach for the selection of input and output variables, to be used for efficiency measurement, was applied. Input Oriented CRS and VRS models of DEA were used to get measures of overall technical, pure technical and scale efficiency measures for both marketability and profitability efficiency, separately. To find whether efficiency scores can predict default, a binomial logistical regression was employed. The actual status variable (failed/ not failed) of banks from Compustat database was taken as dependent variable whereas marketability and profitability efficiency scores were independent variables. The study provided evidence that overall technical profitability efficiency (i.e. the quality of management) is a significant predictor of a large bank's default, while marketability efficiency did not predict default of banks. The findings of this study also indicated that the efficiency of banks is independent of its location and banks should pay close attention to marketability efficiency because the sample banks had low level of marketability efficiency as compared to profitability efficiency. Thus, marketability efficiency is one of the major sources of large banks' inefficiency.

Even though researchers worked to measure efficiency level of Pakistani banks in particular but most of the previous studies are based on traditional ratio analysis. A few of them have applied modern techniques of a frontier approach like Data Envelopment Analysis (DEA), but they considered basic level DEA models (constant return to scale or variable return to scale). For example, Akhtar (2002) analysed the x-efficiency, decomposed into technical and allocative efficiency, of 40 commercial banks in Pakistan, 19 being local and 21 foreign, using DEA, for the year 1998. The author asserted the need to improve the efficiency of Pakistani banks. Ataullah, Cockerill, & Le (2004) compared the influence of financial liberalisation on efficiency level of Indian and Pakistani banks from 1988 to 1998. They employed basic DEA model (VRS and CRS) and noticed an improvement in efficiency due to financial liberalisation. The authors also found the presence of high non-performing loans in banks. Shahid, Rehman, Niazi, & Raoof (2010) applied CRS and VRS DEA models to compare the efficiency of conventional and Islamic banks in Pakistan. They selected a sample of five conventional and five Islamic banks from 2004 to 2009. The authors concluded that no significant difference exists between efficiency level of conventional and Islamic banks. Abbas, Azid, & Hj Besar (2016) compared the efficiency, effectiveness and productivity of the conventional and Islamic banks in Pakistan. The data of 6 Islamic and 27 conventional banks from 2004 to 2009 is used as a sample. DEA scores of efficiency and effectiveness were calculated by using DEA VRS and CRS models which were then regressed with bank specific and environmental factors in the second stage to evaluate the effects of these determinants on these scores. The results show that efficiency was positively related to age, capitalization and loan ratio, while an inverse relationship with profitability and other operating income was found. Industry specific and macroeconomic factors did not have any significant impacts on efficiency level of banks. Similarly, the literature exists regarding default risk estimation of Pakistani banks in specific but most of the researchers used Z score or non-performing loans ratio as the proxy for default risk of Pakistani banks. There is a scarcity of research that used market-based techniques to measure the stability level of Pakistani banks. For example, Abbas, Zaidi, Ahmad, and Ashraf (2014) analysed the impact of credit risk on the performance of banking system of Pakistan. Their data set comprised of a panel of 21 banks from 2006 to 2011. They measured credit risk by the ratio of nonperforming loans to total loans, total loan and advances to total deposits, and loan loss provision to total classified loans. Performance is measured by the ratios of return on assets and return on equity. The results of fixed effect regression showed that an increase of credit risk results in a decrease in the performance level of banks.

Despite the availability of vast literature on efficiency and default risk of banks, there is a scarcity of studies relating default risk and efficiency of financial institutions. Although some previous researchers found evidence regarding a linkage between these two performance parameters, but the authors could not reach a consensus about the relationship. Similarly, the previous studies ignored the link of marketability efficiency and stability of banks. There is also a lack of research in the context of a developing country South Asian region because the relationship between efficiency and stability is mostly researched in the context of developed nations. The studies involving Pakistani banking system in specific involve using less advanced techniques to measure efficiency and default risk and most of them address the variables in isolation. Therefore, the evidence regarding the relationship between default risk and profitability, marketability as well as the overall efficiency by utilising advanced techniques of measurement will provide significant insights into the unique features of the banking system of a developing country of South Asia where both Islamic and conventional system coexist.

2.1. Proposed Hypotheses

Based on the review of the existing literature, following hypotheses are specified:

H 1. There exist a significant relationship between overall efficiency and default risk of banks.

H 2. There exist a significant relationship between profitability efficiency and default risk of banks.

H 3. There exist a significant association between marketability efficiency and default risk of banks.

CHAPTER 3

METHODOLOGY

The present study adopts a three step procedure to analyse the existence and nature of the relationship between default risk and efficiency of the banking firms. First, Merton’s distance to default model is used to estimate the default risk. Second, the efficiency of banks is measured by adopting a production perspective. The production process of the bank is viewed as a system which is decomposed into two sub processes involving inputs, intermediaries and outputs. Profitability efficiency scores are obtained from the first stage while marketability scores are obtained from the second stage, and overall efficiency scores are obtained by using the inputs of the first stage and outputs of the second stage. The scores are calculated following two-stage efficiency decomposition process of Kao and Hwang (2008) which accounts for the series relationship of the two sub-stages of the overall process. Then, Panel VAR approach is used to analyse the relationship between profitability efficiency and default risk, marketability efficiency and default risk as well as overall efficiency and default risk of banks.

For the sake of robustness, efficiency scores are calculated without accounting for the series relationship and considering the independency of the whole production process and its two sub-stages, following the process used by Luo (2003); Seiford and Zhu (1999); and Sohail and Anjum (2016). Then panel VAR is applied to analyse the relationship between efficiency scores obtained through this procedure and default risk of banks. Results obtained from both methods are then interpreted and analysed.

3.0. Population and Sample of the Study

All of the thirty three commercial banks of Pakistan comprise the population of the current study. Pakistani banking sector is comprised of thirty seven banks, out of which thirty three are commercial banks, and four are specialized banks. There are six foreign commercial banks, and twenty seven local commercial banks. Local commercial banks are further divided into twenty two private banks, and five public sector banks (State Bank of Pakistan, 2014). However, sample comprised of twenty two listed commercial banks of Pakistan due to the listing requirement. Three public sector and nineteen private sector banks are included in the sample. The study period is eleven years from 2004 to 2014. Data sources are DataStream, Banking Statistics of Pakistan, Financial Statement Analysis of Financial Sector prepared by State Bank of Pakistan and annual reports of the banks.

3.1. Default Risk

The present study utilises Merton's distance to default model to calculate default risk of banks. The likelihood of default of a counterparty on a payment (mostly related to loans or corporate bonds) is termed as credit risk. That is the risk that an obligor would not be able to meet its obligations on specified time. These obligations can be of various forms, for example, the repayment of debt. Credit risk is sometimes termed as default risk, and these terms are used interchangeably in the present study. Default risk of a firm is the risk that the firm would not be able to repay its debts and fulfil its obligation.

A number of techniques have been developed in the last twenty-five years to measure default risk of banks. These techniques are usually classified as accounting based techniques, market-based techniques and external rating agencies. (Allen & Powell, 2011). Altman's Z-score, NPL (Non-performing loans) analysis and Olson's O score fall under the category of accounting based techniques. Some external credit rating agencies for example Standard and Poor's, Fitch and Moody's also estimate credit ratings based on the credit risk of financial firms. However, techniques utilising market-based indicators are considered the most contemporary and sophisticated methods which include Merton's DD (distance to default) model, CreditMetrics™ and VaR (Value at Risk).

Use of market information for measuring default risk of banks has numerous benefits. First, equity prices are accessible at high frequencies. Normally banks are listed on stock exchanges, and it is very convenient to collect the data of their daily stock prices. Second, if the market is efficient, then stock prices are the reflection of investors' expectations and forward based information. Third, the transparency and verifiability of these techniques are assured because of no confidentiality issue as the data is available publically.

There are also some limitations in using market-based information: First, the default risk of a bank which is not listed on the stock exchange cannot be calculated. Second, if the market in which stocks of banks are traded are not liquid and transparent, then it will badly affect the accuracy level of the results. Third, there are some assumptions that may not hold in practice. For example the assumption that a lognormal process is followed by asset values. This assumption is inadequate to capture the effect of extreme events. However, despite the limitation, Merton's model of Distance to Default has been widely used in the banking context.

Merton's DD model is the most popular among market-based models to measure default risk (Harada, Ito, & Takahashi, 2010). Using market-based indicators instead of accounting based indicators yield more accurate results because the former shows investor's expectation and forward-looking information whereas the latter reflects past information and is prone to alteration by the management.

In 1993, Moody's KMV devised a technique based on Merton's model for the estimation of a firm's default probability at some specified point in time. This technique applies to the banking firms as well. According to their proposed approach, when the market value of any particular bank's assets declines in such a way that it becomes less than the book value of the bank's liabilities (short term plus half of the long-term liabilities value), default occurs. Subtraction of the face value of bank's debt from bank's estimated market value results in default probability. The resulting value is then divided by the bank's estimated volatility which results in a figure like Z score. This score is called distance to default (DD). The distance to default is, in essence, the number of standard deviations of market value a particular bank is away from the point of default.

The Merton (1974) model is the foundation of Moody's KMV model. If Merton's model is considered in the context of banking firms in the setting of the present study, then equity of a bank can be treated as a call option on the bank's assets, provided the fact that shareholders have the residual claim on bank's asset after the settlement of all liabilities. The book value of the bank's liabilities is the strike price of the call option. If the bank's asset value fall below than the strike price, then the value of the equity would be zero.

There are two important assumptions of the model to take into account. First, the total market value of a bank's assets follow a geometric Brownian motion:

$$dVB = \mu V_B dt + \sigma_B V_B dW \tag{1}$$

In the above equation, μ is periodic rate of return (ROR) on the assets of the bank (which is expected and instantaneous), V_B denotes the asset value of the bank, σ_B is asset volatility or standard deviation (instantaneous) of assets' ROR while dW denotes standard Weiner process.

Second, a single discount bond with a maturity of T time periods is issued by the bank. The bank's equity is considered a call option on the underlying assets' value of the bank. Equity strike price is V_B which is equal to the bank's debt face value and time to maturity (T). If V_E denotes the equity's present market value then according to option pricing formula proposed by Black and Scholes (1973):

$$V_E = V_B N(d_1) - X_e^{-rT} N(d_2) \tag{2}$$

Where:

$$d1 = \frac{\ln\left(\frac{V_B}{X}\right) + \left(r + 0.5\sigma_B^2\right)T}{\sigma_B\sqrt{T}} \tag{3}$$

In the above mentioned equation: r denoted risk free rate, σ_B is the bank's asset volatility and N denotes cumulative density function of standard normal distribution. While:

$$d_2 = d_2 - \sigma_B\sqrt{T} \tag{4}$$

For the calculation of distance to default, information regarding value and volatility of equity is required. According to Eq. (2), equity value can be considered as a function of the bank's value. Considering another assumption of Merton's model in banking firms' context, equity value can be regarded as a function of bank value and time,

$$\sigma_E = \left(\frac{V_B}{E}\right)\frac{\partial E}{\partial V}\sigma_B \tag{5}$$

However, according to Black Scholes Merton model: $\partial E/\partial V = N(d_1)$, therefore, the relationship between bank volatility and its equity can take the following form:

$$\sigma_E = \left(\frac{V_B}{E}\right)N(\mathrm{d}1)\sigma_B \tag{6}$$

Thus, the distance to default is:

$$DD_t = \frac{\ln\left(\frac{V_{B,t}}{X_t}\right) + \left(\mu - \frac{1}{2}\sigma_B^2\right)T}{\sigma_B\sqrt{T}} \tag{7}$$

In the above equation, V_B denotes assets' value, μ is expected return on assets, σ_B denotes assets volatility, T denotes time period while X_T is value of liabilities.

As for as value of liabilities is concerned, in Merton's model, total value of liabilities is regarded as the terminal value of assets. However, Moody's KMV has modified Merton's model by considering default point as the summation of short term plus half (1/2) of long term liabilities. This modification is proposed after observing from a large sample of firms that when their asset value decline to a critical point which lies somewhere between the value of total debt and short term debt, the firms default. The default probability is:

$$PD = N(-DD) \tag{8}$$

Where N denotes cumulative probability distribution.

The information regarding market value of assets, assets volatility and expected return on assets is not known in advance. This information can be derived by using equation (2) and equation (6). The following steps are taken to calculate distance to default:

In order to solve equation (7), in the first step, the volatility of equity is estimated. Equity volatility ($\sigma_{E)}$ can be calculated by using historical stock prices of a public listed company. The methodology proposed by Hull (1999) is used, according to that methodology:

$$R_i=\ln(pr_t\text{-}pr_{t-1}) \tag{9}$$

In the above equation: R_i denotes the daily stock price returns where pr_i is closing stock price while (i = 1, 2, 3,…., n).

Annual volatility is calculated by using the following equation:

$$\sigma_E = \frac{1}{\sqrt{\frac{1}{n}}}\sqrt{\frac{1}{n-1\sum_{i-1}^{n} r_i^2}} - \frac{1}{n(n-1)}\left(\sum_{i-1}^{n} r_i\right)^2 \tag{10}$$

In the above equation, n denotes the number of trading days in a year. After inserting equity's market value (V_E) as the product of share price and number of outstanding shares, liabilities value (X_t) as short term liabilities value plus half of the value of long term liabilities, and risk free rate (r) as return on treasury bills in Equation (2) and Equation

(6); the assets' market value, volatility and expected drift are estimated. These values are then used in Equation (7) to arrive at the figure of distance to default (DD). Distance to default is calculated using the excel solver routine, that very routine is used by Kabir, Worthington and Gupta (2015).

The number of standard deviations the asset value is away from the default point is termed as distance to default (DD). "It is defined as the distance between the default point and firm's expected assets value at the analysis horizon, which is normalized by standard deviation of the future asset returns" (Ong, 2005, p. 81). The higher the distance to default score, the farther is the firm (bank) value from the default point, and the lower will be the default probability.

3.1.1. Distance to default variables

Market value of assets, leverage and asset risks are considered the chief determinants of DD (distance to default). The definition and description of the variables of distance to default are presented in Table 1. Banks' stock prices data is downloaded from DataStream and data regarding the number of outstanding shares of the banks is taken from Pakistan Stock Exchange website. Treasury bill rate per annum is used for rate of return which is derived from International Monetary Fund (IMF) website. Liabilities are derived from Financial Statements Analysis of Financial Companies prepared by State Bank of Pakistan while Financial Statements of individual banks are also consulted for missing data. All liabilities are considered to be due in one year (T=1).

Table 1. Variable definitions and sources of data for the calculation of DD

Variable	Definition	Description and Data Sources

σ_E	Volatility of equity	Annualized volatility of stock prices with daily frequency
V_E	Value of equity (Market capitalization)	Stock price × Number of outstanding shares (DataStream and Pakistan Stock Exchange)
X	Total liabilities	Short term liabilities + half of long term liabilities (Financial Statements of banks)
R	Risk free rate	Treasury bill rate (per annum) (IMF website)
V_B	Market value of assets	Author's calculation
σ_B	Volatility of assets	Author's calculation
μ	Expected return on assets	Author's calculation

3.2. Efficiency

Efficiency has been measured by using Data Envelopment Analysis (DEA) which is a non-parametric approach to measure efficiency. DEA was introduced by Farrell (1957) then Charnes, Cooper and Rhodes (1978) extended this approach to measuring efficiency by introducing Constant Return to Scale (CCR or CRS) model. After the extension proposed by Charnes et al. (1978), DEA is widely being applied for the measurement of efficiency, in relative terms, of a group of decision making units (DMUs) which are using similar inputs to produce similar outputs. The results show the relative efficiency of each decision making unit as compared to other decision making units regarding the conversion of inputs to outputs.

Many techniques are proposed in order to estimate efficiency scores using frontier approaches. However, two techniques have attained popularity for measuring efficiency in the context of the banking sector. These techniques are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Sena (2003) argues that it is not possible to prefer one technique over the other because both techniques have pros and cons. Stochastic Frontier Analysis consider inclusion of statistical noise in the frontier, it also permits statistical tests on the estimates. However, data envelopment analysis is beneficial in the sense that it is not required to specify any functional form for production function (i.e. in order to determine the most efficient decision making units). Similarly, it is not required to specify a distributional form for the terms of inefficiency. Furthermore, data envelopment analysis is preferred over other frontier techniques when the sample size is small (Pasiouras 2008). On the other hand, data envelopment analysis is based on the assumption that there are no measurement errors in the data. DEA is also highly sensitive to the outliers.

Despite its shortcomings, DEA has been widely applied to measure efficiency due to fewer requirements as compared to SFA. Liu, Lu, Lu & Lin (2013) conducted a survey about DEA applications and found that even though DEA techniques have been widely used in twenty five industries but the fifty percent of DEA studies involve top five industries. Among these top five industries, the banking industry is at the top by size and magnitude of the DEA studies. DEA applications in banks are about fifteen percent of all studies,

A banking firm performs various operations which can be viewed as a system and further decomposed into two stages. For example, a bank's production process takes input in the form of employees, equity and assets to generate profits and revenues which in turn become inputs of the second stage and transforms them into market value, share price and earnings per share of the second stage. Thus a technique is needed in order to disclose inefficiencies in each stage of the process. In recent years, extension in the data envelopment analysis are proposed in order to examine the efficiency of the processes which can be decomposed into two stages, the outputs of the first stage are considered intermediaries and used to produce second stage outputs. In this way, efficiency scores of the first, second and overall stages are provided by the resultant two stage data envelopment analysis model.

In the present study, a two stage production process is used to estimate the efficiency of the banks; the first stage corresponds to profitability efficiency and the second stage corresponds to marketability efficiency. The outputs of the first stage are considered intermediaries and these are treated as inputs in the second stage. This resultant model provides overall efficiency scores of the process as well as efficiency scores of stage one and stage two.

Efficiency scores are obtained by using two types of models for the two stage process. First, by applying the approach developed by Kao and Hwang (2008) in which the serial relationship between the two sub-processes is accounted for. Second, the efficiency scores are calculated by using an independent model for two stage process in line with Luo (2003), Seiford and Zhu (1999). This independent model is also used in some recent studies (Lo & Lu, 2006; Lo, 2010; Lu & Hung, 2009; Shahwan & Hassan, 2013; Sohail & Anjum, 2016).

In the independent model, three independent models yield the efficiency scores of the first and second stage, as well as of the whole production process.

If Xij, (i =1, ... ,m) and Yrj, (r =1, ... , s) are the ith input and rth output of DMUj, (j =1, .. . ,n). Then, in order to measure efficiency, the conventional data envelopment analysis model based upon the assumption of constant return to scale for the decision making unit “k” can be expressed in the form of the below mentioned equation (Charnes et al., 1978):

$$E_k = Max\frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{i=1}^{m} v_i X_{ik}} \tag{11}$$

s.t. $\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1$, j=1,…,n,

u_r, v_i, $\geq \varepsilon$, r =1,…,s; i=1,…,m,

According to Charnes and Cooper (1984), "ε" denotes a very small non Archimedean number. Each decision making unit uses m inputs in order to generate s outputs, and Ek denotes the relative efficiency of the decision making unit "k", if the of less than one will show inefficiency. If we assume a production process of a bank then the whole process comprises of two sub stages. The overall process "k" utilizes "m" inputs X_{ik}, (i =1,..., m) that yield in "s" outputs Y_{rk}, (r =1,..., s). Now as it is assumed that production process is comprised of two stages, thus, the outputs of the first sage are considered q intermediate products Z_{pk}, (p =1,..., q) which are treated as inputs of the second stage. The independent two stage DEA model uses conventional model to estimate the overall efficiency E_k (e.g., Luo, 2003). Following models will be used to estimate efficiency ratios of the first stage and the second stage, E_k^1 and E_k^2 respectively:

$$E_k^1 = Max \frac{\sum_{p=1}^{q} w_p Z_{pk}}{\sum_{i=1}^{m} V_i X_{ik}} \tag{12}$$

s.t. $\frac{\sum_{p=1}^{q} w_p Z_{pj}}{\sum_{i=1}^{m} V_i X_{ij}} \leq 1$, j=1,…,n,

w_p, v_i, $\geq \varepsilon$, p =1,…,q; i=1,…,m,

$$E_k^2 = Max \frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{p=1}^{q} w_p Z_{pk}} \tag{13}$$

s.t. $\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{p=1}^{q} w_p Z_{pj}} \leq 1$; j=1,…,n,

u_r, w_p, $\geq \varepsilon$, r =1,…,s; p=1,…,q.

The conventional models are used to estimate efficiency of the two stages and it is assumed that no relationship exist between the efficiencies of the whole system and two sub stages, thus, efficiencies of all of the three stages are estimated independently.

However, Kao and Hwang (2008) accounted for the serial relationship between efficiency scores of the two stage process and proposed a technique which decomposes overall efficiency into the product of the efficiency of the two sub processes. This technique not only provides overall efficiency scores but also the efficiency scores of the each sub-stage. In the second stage, the efficiency of the first stage is maximized and the constraint is to maintain that same level for the overall efficiency score. Following this concept, multiplication of the efficiency scores of the two sub stages results in overall efficiency score. The mathematical relationship between the efficiency scores of the overall process and two sub processes is justified according to the generic expectation of the public about the physical relationship between a whole system and its parts.

If relational model is considered and it is assumed that there are "n" DMUs (which are banks in this study) that have a two stage production process. In the first stage, each decision making unit DMU_j, where j= 1,2, .. . ,n, has i inputs X_{ij} (i=1,2,... ,m), and the outputs of the first stage are q outputs, Z_{pj} (p= 1,2, .. . ,q). These Z outputs are considered intermediaries and these are inputs to the second stage while $Y_{rj,}$ where r= 1,2, ... , s, are the outputs from the second stage.

The first stage efficiency ratio for a decision making unit "k" is denoted by E_k^1 while E_k^2 denoted efficiency ratio for the second stage:

$$\mathrm{E}_k^1 = \frac{\sum_{p=1}^{q} w_p Z_{pj}}{\sum_{i=1}^{m} V_i X_{ij}} \tag{14}$$

$$\mathrm{E}_k^2 = \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{p=1}^{q} \hat{w}_p Z_{pj}} \tag{15}$$

In the above equations, v_i, w_p, $\hat{w}_p$, and u_r denote non-negative weights. Kao and Hwang (2008) report that $w_p=\hat{w}_p$. Consequently, overall efficiency the two-stage overall efficiency ratio E_k is defined as $E_k^1 \times E_k^2$, which is equal to:

$$E_k = \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io}} \tag{16}$$

To calculate the overall efficiency "E_k", the relational model will be as follows:

$$Max\ E_k^1 \times E_k^2 = \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} v_i X_{io}} \tag{17}$$

s.t. $E_k^1 < 1$ and $E_k^2 \leq 1$ and $w_p=\hat{w}_p$

The above mentioned model proposed by Kao and Hwang (2008) can be converted into linear program by the application of usual transformation:

Max $\sum_{r=1}^{s} u_r Y_{ro}$

s.t. $\sum_{r=1}^{s} u_r Y_{rj}$ - $\sum_{p=1}^{p} w_p Z_{pj} \leq 0$, j=1,2,…,n,

$\sum_{p=1}^{p} w_p Z_{pj}$ - $\sum_{i=1}^{m} V_i X_{ij} \leq 0$, j=1,2,…,n,

$\sum_{i=1}^{m} V_i X_{ij}=1$,

$W_p \geq 0$, p=1,2,…,q; $V_i \geq 0$, i=1,2,…,m; $U_r \geq 0$,r=1,2,…,s.

Then efficiency scores are determined using input-oriented approach. Input oriented instead of output oriented DEA models are widely used in banking studies. The use of input oriented approach is justified based upon the assumption that the management of banks have more control over input as compared to outputs (Fethi & Pasiouras, 2010).

3.2.1 Specification of DEA inputs and outputs

Despite a plethora of DEA studies in the banking sector, no clear agreement exist regarding the input and out variables to be used to calculate efficiency (Avkiran, 2011). In order to specify proper inputs and outputs, generally two perspectives are used in the context of banking firms: the production approach and the intermediation approach (e.g. Yue, 1992; Luo, 2003; Avkiran, 2011). Seidord and Zhu (1999) defines banks from the perspective of production approach as producers of services by processing deposits and loans. In contrast, banks are defined as financial intermediaries that borrow funds from the surplus units and lend them to the deficit units (Mohd Tahir, Abu Bakar, & Haron, 2009). The design of the present study adopts the two stage production process for commercial banks which is in line with the study of Luo (2003). Specifically, the production approach is adopted in defining inputs and outputs for banks.

Negative values of input and output variables are not omitted. Instead, variant radial measure (VRM) proposed by Cheng, Zervopoulos, and Qian (2013) is used to treat negative data. The choice of VRM model instead of other models is justified due to the shortcomings of the previous models. For example, the (normalized) additive model proposed by Lovell and Pastor (1995) does not provide efficiency measure. The Semi-Oriented Radial Measure (SORM) developed by Emrouznejad, Anouze, and Thanassoulis (2010) may select inappropriate targets to be achieved. The Range Directional Measure (RDM) proposed by Portela, Thanassoulis, and Simpson (2004), can be unbounded if the DMU under consideration has minimum values for inputs and maximum levels for outputs. However, in variant radial measure model, in order to reach at best practice frontier, the absolute values are inserted in place of the original values which quantifies the proportion of improvements. The VRM model is units invariant. Additionally, the proportionate improvement property of the traditional radial model is preserved in this model. The variant radial measure model provides similar results with the traditional model in those cases where traditional model is applicable.

Figure 1 shows the model adopted to measure efficiency. Three dimensions of efficiency are shown in the figure. The first dimension measures profitability efficiency by involving three inputs (number of employees, total assets, equity) and two outputs (revenues and profits), this is the first stage of the production process. The second dimension measures marketability efficiency using two inputs (revenues and profits) and three outputs (market value, earnings per share, and stock price). The third dimension corresponds to overall efficiency involving three inputs (number of employees, total assets, equity) and three outputs (market value, earnings per share, and stock price).

Figure 1. Bank's Production Process

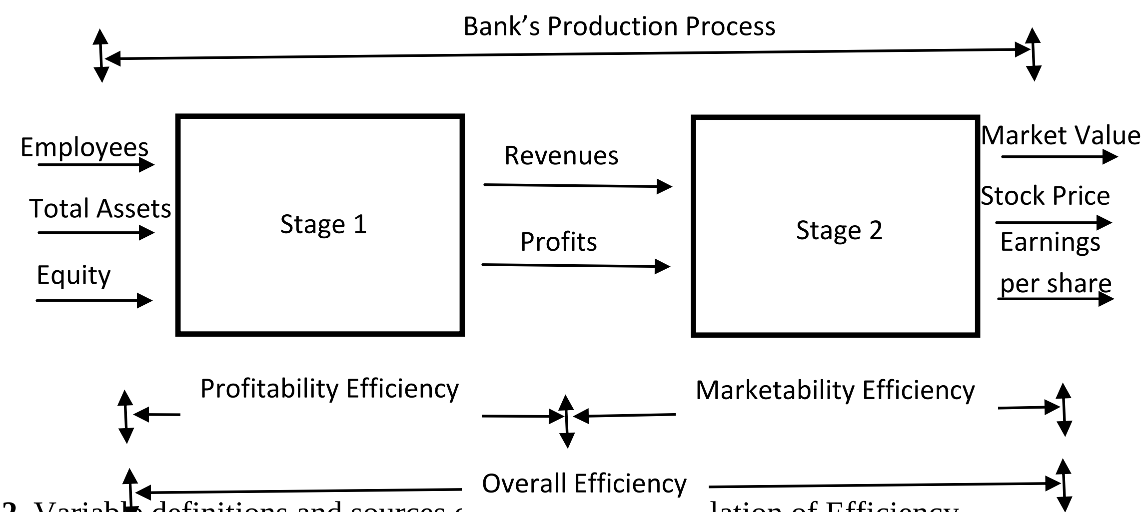


Table 2. Variable definitions and sources of data for the calculation of Efficiency

Variable	Definition	Description and Data Sources
X1	Employees	Number of employees
X2	Total Assets	Short term plus long term assets

X3	Equity	Book value of equity
Z1	Revenues	Revenues of the bank
Z2	Profits	Net Profit of the bank
Y1	Market value	Outstanding shares× market price
Y2	Stock price	Closing stock price at the end of the period
Y3	Earnings per share	Net profit / No. of outstanding shares

Data sources: Financial statement of banks and various issues of Banking Statistics of Pakistan

3.3. Panel VAR

Panel Vector Autoregressive model (pVAR) is applied to analyze the inter relatedness of default risk and efficiency (profitability, marketability and overall efficiency) of the banks. Panel VAR is estimated using a package of programs to estimate pVAR in Stata developed by Abrigo and Love (2015). The program is based upon a generalized method of moments (GMM) framework.

A k-variate Panel Vector Autoregressive model with p lag order and panel specific fixed effects is described by Abrigo and Love (2015) by a system of the below mentioned linear equations:

$$Y_{it}=Y_{it-1}A_1+ Y_{it-2}A_2+\ldots+ Y_{it-p+1}A_{p-1}+ Y_{it-p}A_p+ X_{it}B+u_{it}+e_{it} \qquad (18)$$

$i=(1, 2,\ldots,N)$, $t=(1,2,..,T_i)$

In the above mentioned equation: Xit is a (*1xl*) vector of exogenous covariates, and Y_{it} is a (*1xk*) vector of dependent variables; is (*1xk*) vector of dependent variable-specific fixed-effects and eit is a (*1xk*) vector of idiosyncratic errors. A_1, A_2, … , Ap-1, Ap is a *(kxk*) matrix of the parameters to be estimated and the (*lxk*) matrix B is also the matrix of unknown parameters. The innovations have the following characteristics $[eit] = 0$, $[e'it, eit] = S$ and $[e'it, eis] = 0$, for all $t>s$.

All of the variables in a panel VAR setting are considered endogenous variables. A multivariate panel regression is fit by the panel VAR model of each endogenous variable on its lags and on lags of other endogenous variables by following generalized method of moments (GMM) framework via forward orthogonal deviation (FOD) transformation (Abrigo & Love, 2015). Forward orthogonal deviation deducts the mean of future observations instead of making use of deviations from past realizations of each variable, which makes past realizations valid instruments. Model estimation by Abrigo and Love (2015) is robust to heteroskedasticity.

The structure of the two equation VAR framework used to model efficiency (profitability efficiency, marketability efficiency and overall efficiency) and distance to default (DD) is stated below:

$$Eit=E_{it-1}A_1+ E_{it-2}A_2+\ldots+E_{it-p+1}A_{p-1}+ E_{it-p}A_p+ DD_{it}B+u_{it}+e_{it} \qquad (19)$$

$$DDit=DD_{it-1}A_1+ DD_{it-2}A_2+\ldots+DD_{it-p+1}A_{p-1}+ DD_{it-p}A_p+ E_{it}B+u_{it}+e_{it} \qquad (20)$$

i=(1, 2,…,22), t=(1,2,..,11)

Where Eit represents profitability, marketability and overall efficiency and DDit captures distance to default.

Impulse response functions (IRFs) and variance decompositions (VDCs) are estimated from the analysis after solving a complex identification problem. In VAR, impulse response function estimates the effect of a structural shock in one of the variables on future expected values of the other, ceteris peribus. Thus, conditional forecasts of the dependent variable that evolve with the passage of time are recorded by impulse response functions.

In order to identify the interdependencies between efficiency and default risk, three panel VAR models are run separately. First, a panel VAR model is adopted to examine the inter relatedness of overall efficiency and default risk, followed by the panel VAR framework to examine the interaction between profitability efficiency and default risk and finally panel VAR is applied to analyse the inter-relationship of marketability efficiency and default risk of the banks. Given that two types of models are used to measure efficiency, thus, each panel VAR model is repeatedly run by using efficiency scores obtained from two types of models. First, the efficiency scores obtained by using the model of Kao and Hwang (2008) are used in panel VAR analysis. Then, for the sake of robustness, the efficiency scores in panel VAR models are replaced by the scores obtained from the independent model in line with Luo (2003). The results of panel VAR analysis after replacement of efficiency scores are then analysed and compared with the results derived from panel VAR analysis which uses efficiency scores derived from relational two stage model of Kao and Hwang (2008). The results obtained are then interpreted and discussed.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1. Descriptive Statistics

Table 3 shows descriptive statistics of variables used to calculate the distance to default. The table displays mean, standard deviations, minimum and maximum values of variables. Risk-free rate, the value of liabilities and value of equity are used to calculate the distance to default while volatility of equity, market value of assets, volatility of assets are calculated through a quadratic optimisation technique, Distance to Default (DD). The risk-free rate is annual Treasury bill rate with a mean value of 0.10 and standard deviation of 0.02. The rate ranged from 0.2 to 0.12 from 2004 to 2014. The value of liabilities and value of equity are stated in terms of thousand Rupees (Rs.). The mean value of liabilities is 149003113.10 and deviation from mean value is 160645477.00. The liabilities of all banks lie in the range of 1047808.50 to 911150793.00 from 2004 to 2014. However, the mean value of equity is low as compared to liabilities and VE is 37898472.31 with a standard deviation of 57673456.41. The equity of all banks lies in the range of 1045947.76 - 340197833.50 from 2004 to 2014. The market value of assets has an average value of 171690806.00 with a standard deviation of 192879043.90. The value ranges from 2939186.92 to 1146369565.00, which means banks differ in size. Asset volatility is 0.14 with 0.31 as the deviation from mean value and it varies from 0.01 to 3.19. The expected return on assets is quite low having a mean value of 0.02 and standard deviation of 0.19. The value varies from -0.9 to 1.04. Distance to default is small for Pakistani banks with an average of 1.21 with a standard deviation of 2.55. It varies between 7.07 to -9.27 showing the banks differ in the level of riskiness.

Table 3. Distance to default variables

Variables	Mean	Standard Deviation	Maximum	Minimum
Risk free rate (r)	0.10	0.02	0.12	0.02
Value of liabilities (X)	149003113.10	160645477.00	911150793.00	1047808.50
Value of equity (V_e)	37898472.31	57673456.41	340197833.50	1045947.76
Volatility of equity (σ_E)	0.54	0.36	3.43	0.23
Market value of assets (V_B)	171690806.00	192879043.90	1146369565.00	2939186.92
Volatility of assets (σ_B)	0.14	0.31	3.19	0.01
Expected return on assets (μ)	0.02	0.19	1.04	-0.90
Distance to default (DD)	1.21	2.55	7.07	-9.27

*Value of liabilities, value of equity and market value of assets are stated in terms of Thousand Rupees. Percentage is the unit of risk free rate, equity volatility, asset volatility and expected return on assets. Distance to default is unit less.

Table 4 displays year wise mean, standard deviation, minimum and maximum values of distance to default of the sample banks. Distance to default mean value becomes negative in the period global financial crisis in 2008; it improves in 2009 then becomes negative in 2010 and 2011. In 2011, the lowest minimum and maximum values and the highest deviation from mean value were observed whereas the mean value is -1.75. After 2011, the distance to default mean value gradually increases.

Table 4. Distance to Default (DD) by year

Year	Distance to Default (DD)			
	Distance to default			
	Mean	Standard Deviation	Minimum	Maximum
2004	3.77	1.07	1.86	5.73
2005	3.97	1.56	1.92	7.07
2006	1.78	0.91	-0.49	3.31
2007	2.80	1.25	0.37	5.52
2008	-1.57	1.41	-4.06	2.42
2009	0.98	1.23	-2.01	3.70
2010	-0.08	2.29	-4.07	4.22
2011	-1.75	2.82	-9.27	1.50
2012	1.30	2.23	-3.76	6.10
2013	1.61	2.56	-3.60	5.28
2014	2.34	1.62	0.05	5.77

Table 5 displays efficiency input and output variables used to calculate profitability, marketability and overall efficiency through two types of models. X1, X2 and X3 are considered inputs, Z1 and Z2 as intermediate and Y1, Y2 and Y3 are the outputs.

Table 5. Efficiency Input and output variables

Variables	Mean	Standard Deviation	Minimum	Maximum
No. of Employees (X1)	5567.951	4852.996569	236	17153
Total Assets (X2)	301000000	334653181.8	4024674	1867003389
Equity (X3)	27341557	34382851.67	1279045	160663530
Revenue (Z1)	11029370	14083734.53	-3380662	69086854
Profits (Z2)	3813428	6731247.195	-10112114	31819590
Market Value (Y1)	2270000000	33358639088	1045947.76	4.98187E+11
Stock price (Y2)	47.30489	63.05923085	1.10000002	399.9500122

Earnings per share (Y3)	4.581037	7.266401505	-19.02	24.47

* Total assets, equity, revenue, profits and market value are stated in terms of Thousand Rupees. Stock price and earnings per share are reported in Rupees.

Table 6 shows descriptive statistics of efficiency scores for the whole sample period (2004-2014). According to the results of independent two stage model, the mean of the profitability efficiency is approximately 73% whereas the mean of marketability efficiency is comparatively low i.e. 72%. Overall efficiency level is 69% approximately. However, as per the results of relational two stage model, average profitability efficiency score is 62%, marketability efficiency score mean is 55% and overall efficiency score average is 39%. The efficiency scores are quite low from the relational model than from the independent model. Overall, it can be said that Pakistani banks have high level of profitability efficiency than marketability efficiency. The gap between average profitability and marketability efficiency scores is much larger in the relational model than in the independent model. Pakistani banks have low level of efficiency which is depicted by the mean overall efficiency score of 39% as per the mean overall efficiency score of relational model whereas the mean efficiency level is 69% as per the results of independent model.

Table 6. Efficiency Scores for the whole sample period

Efficiency	Mean	Standard Deviation	Minimum	Maximum
Results from Independent Two Stage Model				
Profitability Efficiency	0.729632883	0.283463921	0	1
Marketability Efficiency	0.7164637	0.267351132	-0.35482	1
Overall Efficiency	0.694057408	0.272948296	0.036653	1
Results from Relational Two Stage Model				
Profitability Efficiency	0.622504242	0.343296426	0	1
Marketability	0.551296901	0.322390581	0	1

Efficiency				
Overall Efficiency	0.386558731	0.269528624	0	1

Descriptive statistics of efficiency score from independent two stage model are shown in Table 7a. Profitability efficiency mean scores are lowest in the year 2009 followed by 2010 and 2011. While marketability efficiency mean score is lowest in 2012, followed by 2010 and 2009. Overall efficiency mean scores are lowest in 2010 followed by 2011 and 2013.

Table 7a. Year wise Efficiency Scores from Independent Two Stage Model

Year	Profitability Efficiency				Marketability Efficiency				Overall Efficiency			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
2004	0.73	0.28	0.00	1.00	0.72	0.27	-0.35	1.00	0.69	0.27	0.04	1.00
2005	0.73	0.29	0.00	1.00	0.72	0.27	-0.35	1.00	0.68	0.28	0.04	1.00
2006	0.72	0.29	0.00	1.00	0.72	0.27	-0.35	1.00	0.67	0.28	0.04	1.00
2007	0.73	0.29	0.00	1.00	0.72	0.27	-0.35	1.00	0.65	0.28	0.04	1.00
2008	0.74	0.28	0.12	1.00	0.72	0.26	0.29	1.00	0.79	0.24	0.32	1.00
2009	0.62	0.35	0.00	1.00	0.68	0.27	0.06	1.00	0.62	0.23	0.31	1.00
2010	0.65	0.32	0.00	1.00	0.59	0.33	-0.35	1.00	0.54	0.26	0.16	1.00
2011	0.68	0.32	0.00	1.00	1.00	0.00	1.00	1.00	0.57	0.30	0.19	1.00
2012	0.76	0.25	0.05	1.00	0.55	0.26	0.24	1.00	0.65	0.28	0.21	1.00
2013	0.80	0.21	0.23	1.00	0.78	0.19	0.46	1.00	0.60	0.28	0.12	1.00
2014	0.85	0.17	0.38	1.00	0.75	0.24	0.14	1.00	0.62	0.33	0.04	1.00

Table 7b shows mean, standard deviations, minimum and maximum values of efficiency score from relational two stage model. Relational model provides low efficiency scores in each year as compared to independent model.

Table 7b: Year Wise Efficiency Scores from Relational Two Stage Model

	Profitability Efficiency				Marketability Efficiency				Overall Efficiency			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
2004	0.62	0.34	0.00	1.00	0.55	0.32	0.00	1.00	0.39	0.27	0.00	1.00
2005	0.61	0.35	0.00	1.00	0.54	0.32	0.00	1.00	0.38	0.27	0.00	1.00
2006	0.60	0.35	0.00	1.00	0.53	0.33	0.00	1.00	0.37	0.27	0.00	1.00
2007	0.60	0.36	0.00	1.00	0.52	0.33	0.00	1.00	0.36	0.27	0.00	1.00
2008	0.71	0.27	0.12	1.00	0.61	0.24	0.29	1.00	0.42	0.22	0.10	0.86
2009	0.57	0.36	0.00	1.00	0.51	0.33	0.00	1.00	0.37	0.31	0.00	1.00
2010	0.62	0.34	0.00	1.00	0.47	0.29	0.00	1.00	0.34	0.26	0.00	1.00
2011	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2012	0.74	0.25	0.05	1.00	0.54	0.27	0.20	1.00	0.36	0.20	0.05	1.00
2013	0.73	0.25	0.11	1.00	0.68	0.25	0.18	1.00	0.49	0.26	0.09	1.00
2014	0.73	0.26	0.10	1.00	0.71	0.27	0.14	1.00	0.52	0.28	0.04	1.00

4.2. Results from Panel VAR Analysis

Result from panel VAR analysis of distance to default and profitability efficiency are presented below followed by panel VAR analysis of distance to default and marketability efficiency and distance to default and overall efficiency of banks. Two models (independent two stage model and relational two stage model) are used to measure the three facets of efficiency. The results of panel VAR by using efficiency scores obtained from each model are presented. The results of lag selection criteria and stability test are stated. Results obtained from Granger Causality Wald test, variance decomposition (VDCs) and impulse response functions (IRFs) are interpreted. Panel VAR estimates are stated in Appendix because panel VAR estimates are occasionally interpreted by itself (Abrigo & Love, 2015). Love and Zicchino (2006) and Koutsomanoli-Filippaki et al. (2009) argue that instead of interpreting panel VAR estimates, moving average representation of the VAR as well as the associated impulse response functions and variance decompositions should be interpreted.

4.2.1. Default Risk and Overall Efficiency

In order to analyze the dynamic relationship between default risk and overall efficiency, a panel VAR model between distance to default and overall efficiency is estimated using GMM estimation.

A. Independent Two Stage Model

Results of panel VAR analysis using overall efficiency scores from independent two stage model are presented below. Lag selection criteria and stability test of panel VAR is stated followed by Granger Causality Wald Tests, VDCs and IRFs. DD is used as a proxy for distance to default and E is the proxy for overall efficiency.

A 1. Lag Selection Criteria

The appropriate lag numbers to include in the panel VAR is selected using the model selection criteria of Andrews and Lu (2001) which is based on the GMM estimator.

Andrews and Lu (2001) moment model selection criteria (MMSC) are the measures which determine the "best fit" of the data. The measures are based on Hansen's J statistic of over-identifying restrictions, the sample size, the number of moment conditions as well as the number of endogenous variables. The MMSC-Akaike Information Criterion (MAIC), MMSC-Bayesian Information Criterion (MBIC), and the MMSC-Hannan-Quinn Information Criterion (MQIC) are included in the measures. The MMSC criteria will be minimum for the best fitting model.

Moreover, the coefficient of determination (CD) represents the variation proportion captured by the model of a specific lag order (Abrigo & Love, 2015).

Table 8a reports the results of lag selection criteria. The MBIC and MQIC are minimized as well as the p-value of Hansen's J-statistic is significant with the first-order panel VAR model. The CD is maximized with the first-order model. Hansen's J-statistic declines with increase in the number of lags. This suggest improvement of model fit with increased lag order. This measure does not takes into account degrees of freedom like the MMSC criteria. Thus, less consideration has been paid to this condition regarding model selection (Abrigo & Love, 2015).

Table 8a. Lag selection criteria for pVAR default risk and overall efficiency (independent model)

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.624774	26.29598	0.009745	-30.4327	2.295982	-10.985
2	0.504915	19.91225	0.010673	-17.9069	3.912251	-4.94171
3	0.000308	2.725909	0.604689	-16.1836	-5.27409	-9.70107

A.2. Stability Testing

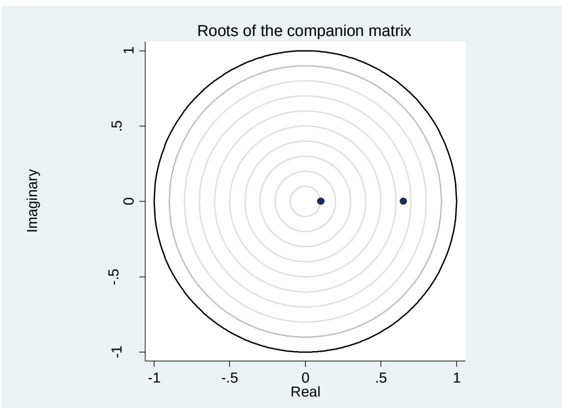
Table 8c shows that modulus of each eigenvalue is less than one, thus, stability condition is satisfied.

Table 8b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.648676	0	0.648676
0.10173	0	0.10173

Figure 2 confirms that the stability condition of the pVAR estimates is met since all eigenvalues of the companion matrix lie inside the unit circle.

Figure 2. Eigenvalues of the Companion Matrix



A.3. Granger Causality Wald Test

Table 8d contains results of Granger Causality Wald Test. Overall efficiency doesn't granger cause distance to default can't be rejected at usual confidence interval. Distance to default does not granger cause overall efficiency can be rejected at 95% confidence interval. On the basis of this result, causality goes from default risk to overall efficiency.

Table 8c. Granger Causality Wald Test

Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	E	2.297	1	0.13
	ALL	2.297	1	0.13
E				

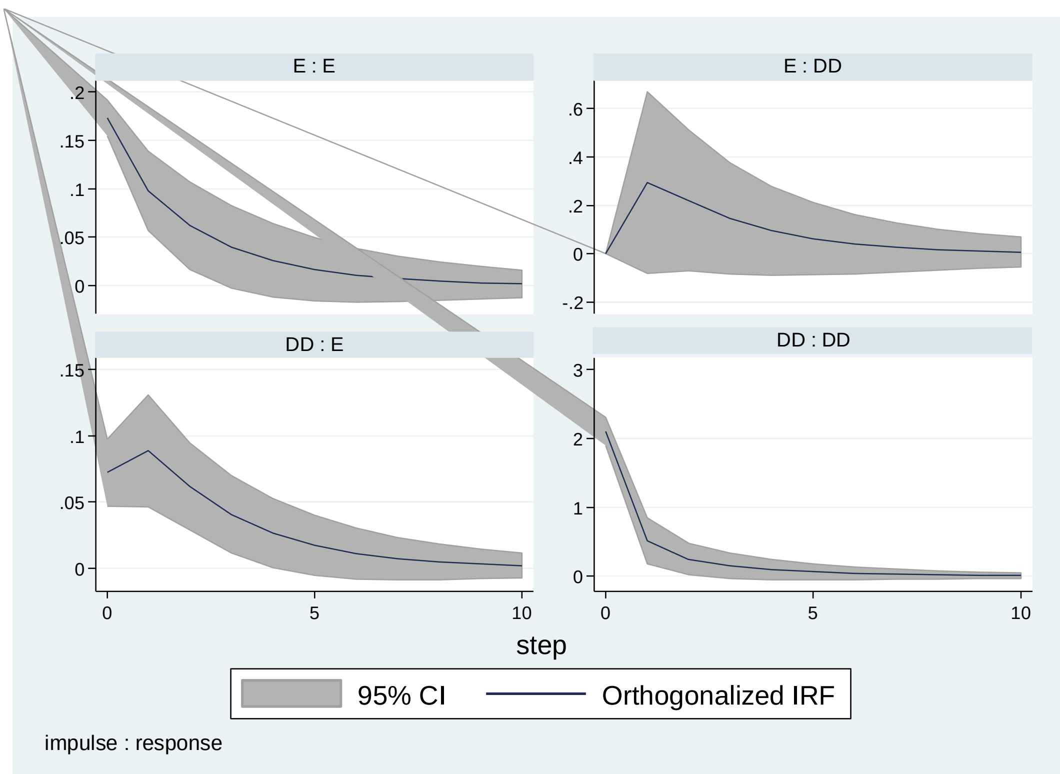
	DD	4.606	1	0.032
	ALL	4.606	1	0.032

A.4. Impulse Response Functions:

Figure 3 displays the orthogonalised impulse response functions obtained after estimating panel VAR model. The 95 percent confidence intervals of the impulse responses are computed using 200 Monte Carlo draws based on the estimated model. From overall efficiency (E) innovation, DD is positively affected but the effect is insignificant and temporal. DD starts converging to equilibrium afterwards. The result implies that an increase in efficiency is followed by decrease in default risk but the decrease is insignificant. The negative relationship between efficiency and risk with the causality direction from efficiency to risk is in line with bad management hypothesis proposed by Berger and DeYoung (1997).

However, DD innovation effect on overall efficiency is significant and positive. A one S.D. shock of DD brings about 29% variation in overall efficiency. Overall efficiency converges to equilibrium after 9th year when one S.D. of shock in DD brings about 1% variation in E. The increase in distance to default means a decrease in default risk. Thus, a decrease in default risk causes an increase in overall efficiency levels of banks. The causality direction from risk to efficiency and their negative relationship is in line with the bad luck hypothesis of Berger and DeYoung (1997) as well as the efficient market hypothesis of Fama (1965).

Figure 3. Impulse Response Functions



A.5. Forecast Error Variance Decomposition

Table 8e displays variance decompositions (VDCs), which show the percentage of the variation in one variable that is explained by the shock in another. 1.8% of variation in DD is explained by shocks in efficiency which increase slightly in subsequent years upto 3.47% in tenth year. However, DD is explaining much larger variation in overall efficiency.14.9 % of variation in overall efficiency is being explained by DD after the first year. The variations gradually increase and upto 30.03% of variation in overall efficiency is being explained by DD. This result implies that overall efficiency is effected by distance to default while there is a weak evidence of reverse causality. The causality direction from risk to efficiency is in line with the bad luck hypothesis developed by Berger and DeYoung (1997) and Efficient Market Hypothesis proposed by Fama (1965).

Table 8d. Forecast Error Variance Decompositions

Response Variable and Forecast horizon	Impulse variable	
	DD	E
DD		
0	0	0
1	1	0
2	0.981863	0.018137
3	0.972284	0.027716
4	0.96819	0.03181
5	0.966476	0.033524
6	0.965758	0.034242
7	0.965457	0.034543
8	0.96533	0.03467
9	0.965277	0.034723
10	0.965254	0.034746
E		
0	0	0
1	0.148772	0.851229
2	0.249322	0.750678
3	0.28111	0.71889
4	0.292637	0.707363
5	0.297172	0.702828
6	0.299025	0.700975
7	0.299795	0.700205
8	0.300117	0.699883
9	0.300253	0.699747

10	0.30031	0.69969

B. Relational Two Stage Model

The results of granger causality tests, VDCs and IRFs obtained from panel VAR analysis of distance to default and overall efficiency are presented in this section. Overall efficiency scores obtained from relational two stage model are used in this analysis. Lag length selection criteria and stability test of panel VAR are also presented.

B.1. Lag Selection Criteria

Optimum lag order of the panel VAR is chosen by using the model selection criteria of Andrews and Lu (2001). Table 9a. shows results of lag selection criteria, MBIC is minimized at first lag. J statistic is significant at first lag while all other conditions are considered less heavily, and for the sake of parsimony, a panel VAR of first order is selected.

Table 9a. Lag selection criteria

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.525762	41.86532	3.51E-05	-14.8633	17.86532	4.584369
2	0.106048	23.15767	0.003168	-14.6614	7.157666	-1.6963
3	0.659208	4.899917	0.297722	-14.0096	-3.10008	-7.52707

B.2. Stability Testing

Table 9b. shows that all eigenvalue modulus is less than unity, thus, pVAR model is stable.

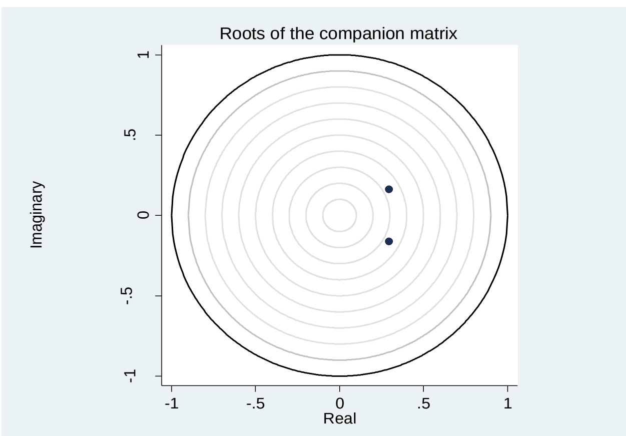
Table 9b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.2949521	0.1620211	0.3365228

0.2949521	-0.1620211	0.3365228

Figure 4 confirms that all the eigenvalues lie inside the unit circle, so, pVAR satisfies stability condition.

Figure 4. Eigenvalues of the Companion Matrix



B.3. Granger Causality Wald Test

Table 9c. contains results of Granger Causality Wald Test. Overall efficiency doesn't granger cause DD is not rejected at usual confidence interval. The DD does not granger cause efficiency cannot be rejected at 95% confidence interval. On the basis of this result, causality goes from default risk to overall efficiency. This result is similar to the result obtained from panel VAR which employs efficiency scores of independent model.

Table 9c. Granger Causality Wald Test

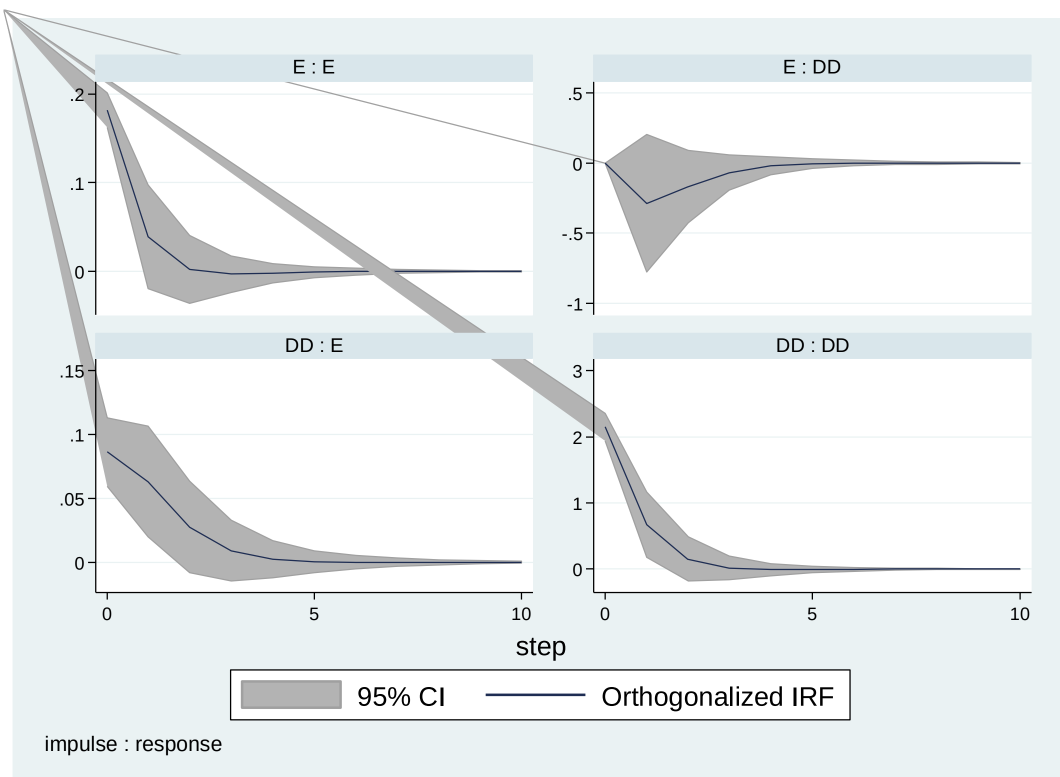
Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	E	1.247	1	0.264
	ALL	1.247	1	0.264
E				
	DD	3.928	1	0.047
	ALL	3.928	1	0.047

B 4. Impulse Response Functions

Figure 5 represnts the orthogonalised impulse response functions. The first row second graph shows that effect of overall efficiency shock on DD is positive but the effect is insignificant and temporal. DD starts converging to equilibrium afterwards. The result implies that there is weak evidence of a negative relationship between overall efficiency and default risk with the causality running from efficiency to risk. This result is in line with bad management hypothesis proposed by Berger and DeYoung (1997).

Whereas, the response of overall efficiency to one S.D. shock of DD is greater. Large variations in overall efficiency are being explained by DD. Overall efficiency converges to equilibrium after 4th year. Thus, a decrease in default risk causes an increase in overall efficiency levels of banks. The causality direction from risk to efficiency and their negative relationship is in line with the bad luck hypothesis of Berger and DeYoung (1997) as well as the efficient market hypothesis of Fama (1965).

Figure 5. Orthogonalised Impulse Response Function



B.5. Forecast Error Variance Decomposition

Table 8e displays variance decompositions (VDCs), which show the percentage of the variation in one variable that is explained by the shock in another. Slight variation i.e. 1.59% in DD is explained by overall efficiency (E) after first year which gradually increase and in the tenth year

2.22% of the forecast error variance of DD is explained by E. However, DD is explaining much higher variation in overall efficiency (E). After first year, 18.39% variation in E is explained by shocks in DD which continues to increase in subsequent years. After sixth year, it started to decline till 8th year. After 9th year, it become constant and DD explains 26.18% percent forecast error variance for E. The result implies that there is strong evidence that causality goes from default risk to efficiency while weaker evidence for reverse causality. The result is similar to the results obtained from panel VAR employing efficiency scores of the independent model, however, the magnitude of variation is smaller as compared to the previous result.

Table 9d. Forecast Error Variance Decomposition

Response Variable and Forecast horizon	Impulse variable	
	DD	E
DD		
0	0	0
1	1	0
2	0.9840496	0.0159504
3	0.978713	0.0212869
4	0.977863	0.022137
5	0.977784	0.0222159
6	0.9777805	0.0222195
7	0.9777805	0.0222195
8	0.9777805	0.0222195
9	0.9777805	0.0222195
10	0.9777805	0.0222195
E		
0	0	0
1	0.1839306	0.8160694
2	0.2485187	0.7514813
3	0.2606041	0.739396
4	0.2618468	0.7381532

5	0.2619019	0.7380981
6	0.261899	0.7381009
7	0.2618987	0.7381013
8	0.2618988	0.7381012
9	0.2618988	0.7381011
10	0.2618988	0.7381011

The results of panel VAR (both in the case of independent model and relational model) confirms the existence of relationship between overall efficiency and default risk of banks, therefore, hypothesis H1 is accepted.

4.2.2. Default Risk and Profitability Efficiency

C. Independent Two Stage Model

Results of panel VAR analysis using profitability efficiency scores from independent two stage model are presented below. Lag selection criteria and stability test of panel VAR is stated followed by Granger Causality Wald Tests, VDCs and IRFs. DD is used as a proxy for distance to default and PE is the proxy for profitability efficiency.

C 1. Lag Selection Criteria

The appropriate lag numbers to include in the panel VAR is selected using the model selection criteria of Andrews and Lu (2001) which is based on the GMM estimator. The results are represented in Table 10a. According to the results, MBIC is minimized at lag order one. J statistics is also significant at lag order one. However, other conditions are considered less heavily and for the sake of parsimony, a panel VAR of first order is selected.

Table 10 a. Lag selection criteria

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC

1	0.755017	34.0152	0.000671	-22.7135	10.01518	-3.26577
2	0.801129	23.5977	0.002676	-14.2214	7.59774	-1.25623
3	0.453592	7.77715	0.100091	-11.1324	-0.22285	-4.64983

C 2. Stability Testing

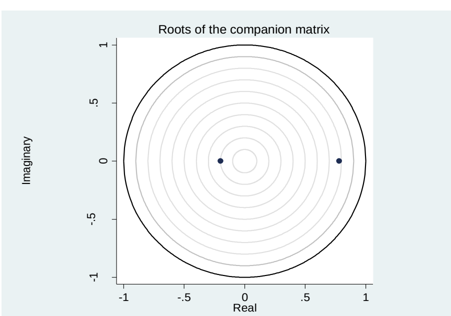
Table 10b. shows that all eigenvalue modulus is less than unity, thus, pVAR model is stable.

Table 10 b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.781772	0	0.781772
0.199757	0	0.199757

Figure 6 further confirms that all the eigenvalues lie inside the unit circle, thus, pVAR satisfies stability condition.

Figure 6. Eigenvalues of the Companion Matrix



C 3. Granger Causality Wald Test

The results of Granger Causality Wald test are represented in Table 10 c. The results provide the evidence of causality and reverse causality between profitability efficiency and default risk.

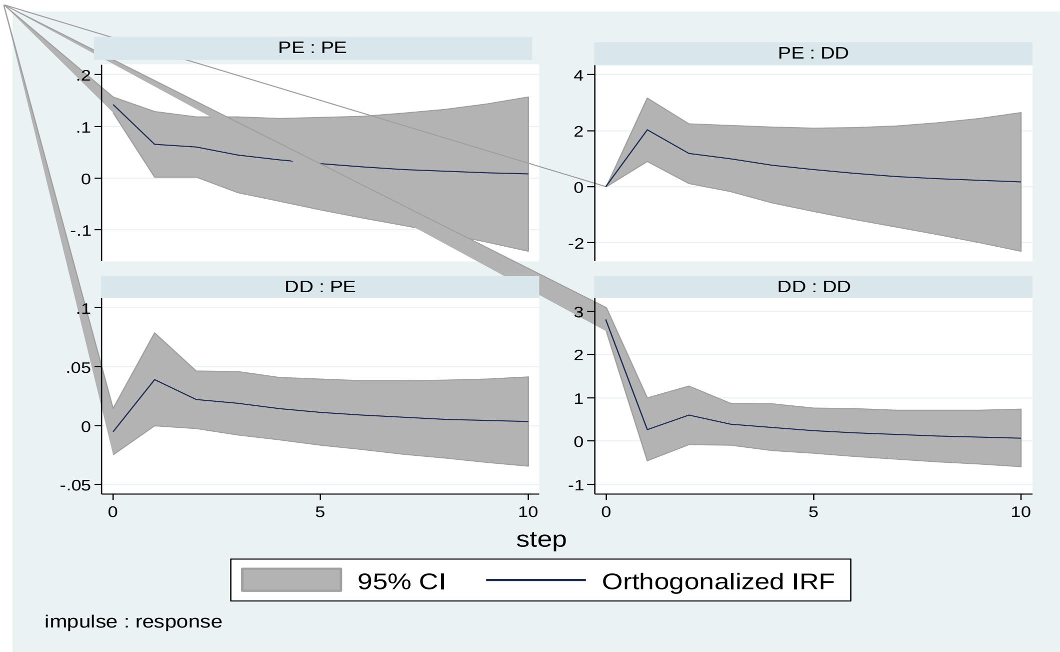
Table 10 c. Granger Causality Wald Test

Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	PE	12.815	1	0
	ALL	12.815	1	0
PE				
	DD	5.74	1	0.017
	ALL	5.74	1	0.017

C 4. Impulse Response Functions

Figure 7 shows that the response of distance to default (DD) to the innovation of profitability efficiency is positive. This result implies that there is negative association between default risk and profitability efficiency and the direction of causality is from efficiency to default risk. However, the confidence interval becomes wider after the first two years. The response of profitability efficiency to distance to default (DD) is positive and temporal, however, the confidence interval is wide. The result implies negative relationship between default risk and efficiency and the causality goes from default risk to efficiency.

Figure 7. Impulse Response Functions



C 5. Forecast Error Variance Decomposition

To further elaborate the analysis, variance decompositions are presented in Table 10 d. which show the percent of the variation in profitability efficiency that is explained by the shock in distance to default and vice versa. These results imply the importance of profitability efficiency of banks in explaining the variation of default risk. Specifically, close to 47.87% of distance to default's forecast error variance after ten years is explained by profitability efficiency's disturbances. This result implies that causality would run from efficiency to risk. On the other hand a small part, less than 8.15%, of the variation of profitability efficiency is explained by distance to default.

Table 10 d. Forecast Error Variance Decompositions

Response Variable and Forecast horizon	Impulse variable	
	DD	PE

DD		
0	0	0
1	1	0
2	0.6581435	0.3418565
3	0.600377	0.399623
4	0.5639246	0.4360754
5	0.5454559	0.4545441
6	0.5347794	0.4652206
7	0.528555	0.4714451
8	0.5248433	0.4751566
9	0.5226106	0.4773895
10	0.5212587	0.4787413
PE		
0	0	0
1	0.0013489	0.9986511
2	0.0605612	0.9394388
3	0.0685055	0.9314945
4	0.0745454	0.9254546
5	0.0774815	0.9225186
6	0.0792037	0.9207963
7	0.0802052	0.9197947
8	0.0808033	0.9191967
9	0.0811631	0.9188368
10	0.081381	0.918619

D. Relational Two Stage Model

The results of granger causality tests, VDCs and IRFs obtained from panel VAR analysis of distance to default and profitability efficiency are presented in this section. Profitability efficiency scores obtained from relational two stage model are used in this analysis. Lag length selection criteria and stability test of panel VAR are also presented. PE is used as proxy for profitability efficiency and DD is used as proxy for distance to default.

D 1. Lag Selection Criteria

The appropriate lag numbers to include in the panel VAR is selected using the model selection criteria of Andrews and Lu (2001) which is based on the GMM estimator. Table 11 a. shows the results of the lag selection criteria. MBIC is minimized at second lag and j value is significant at second lag. Other conditions are relaxed for the sake of parsimony. Therefore, a pVAR of second order is chosen.

Table 11 a. Lag Selection Criteria

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.449512	47.90581	0.00000325	-8.82284	23.90581	10.62486
2	-0.02107	28.87826	0.000333	-8.94084	12.87826	4.024298
3	0.587436	11.88122	0.018257	-7.02833	3.881222	-0.54576

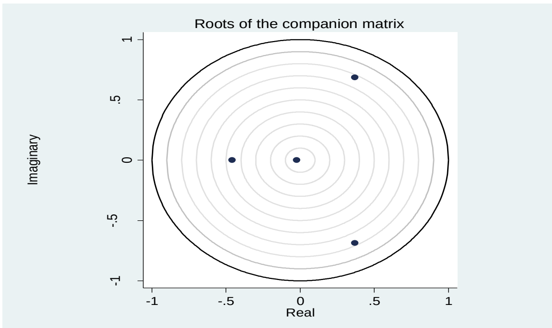
D 2. Stability Testing

Table 11 b. shows that all modulus of each eigenvalue is less than one, hence, stability condition is satisfied.

Table 11 b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.367458	-0.686826	0.778945
0.367458	0.686826	0.778945
0.4600449	0	0.4600449
0.0256216	0	0.0256216

Figure 8: Eigenvalues of the Companion Matrix



According to Figure 8, all the eigenvalues lie inside the unit circle, therefore, pVAR satisfies stability condition.

D 3. Granger Causality Wald Test

Table 11c shows results of Granger Causality Wald Test. Null hypothesis that profitability efficiency doesn't granger cause distance to default can be rejected at usual confidence interval. Similarly, null hypothesis that distance to default does not granger cause profitability efficiency can be rejected at 95% confidence interval. On the basis of this result, causality is bi-directional i.e. from default risk to profitability efficiency and vice versa.

Table 11 c. Granger Causality Wald Test

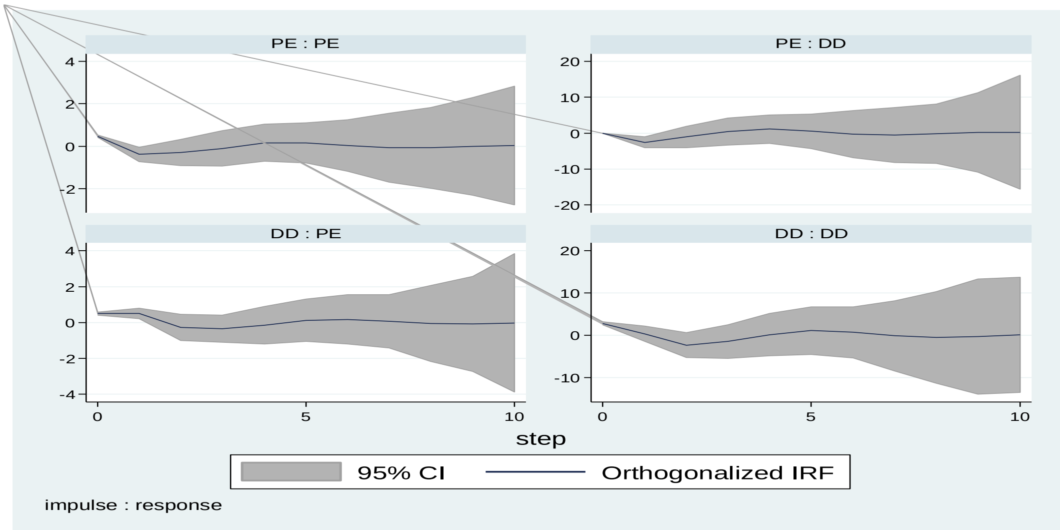
Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	PE	11.001	2	0.004
	ALL	11.001	2	0.004
PE				
	DD	20.425	2	0
	ALL	20.425	2	0

D 4. Impulse Response Functions

IRFs show that there is complex interdependency between profitability efficiency and default risk. DD response to profitability innovation is initially negative then it turns positive, after some time the response repeats this cycle. However, the confidence interval shows the results are insignificant.

The response of PE to DD shock shows opposite behavior. Initially, it is positive and significant then it turns negative and insignificant and it repeats the cycle by turning positive then negative again. The confidence interval becomes wide after first two periods.

Figure 9. Impulse Response Functions



D 5. Forecast Error Variance Decomposition

Variance decompositions (VDCs) are presented in Table 11 d. which show the percent of the variation in profitability efficiency that is explained by the shock in distance to default and vice versa. Close to 35.14% of distance to default's forecast error variance after ten years is explained by profitability efficiency's disturbances. 59.12% of the variation of profitability efficiency is explained by distance to default. This result provides the evidence of bi directional causal relationship between profitability efficiency and default risk.

Table 11 d. Forecast Error Variance Decompositions

Response Variable and Forecast horizon	Impulse variable	
	DD	PE
DD		
0	0	0
1	1	0
2	0.5537375	0.4462626
3	0.6405748	0.3594252
4	0.6698061	0.3301939
5	0.6369185	0.3630815
6	0.6474165	0.3525835
7	0.6517059	0.3482941
8	0.6455238	0.3544762
9	0.6480925	0.3519075
10	0.6486276	0.3513723
PE		
0	0	0
1	0.5229132	0.4770868
2	0.5706958	0.4293042
3	0.5531154	0.4468845
4	0.5923483	0.4076516
5	0.5889539	0.4110461
6	0.5826587	0.4173413
7	0.5919151	0.408085
8	0.590296	0.4097039
9	0.5892102	0.4107898
10	0.5912834	0.4087166

The results of panel VAR analysis show that there exit a relationship between default risk and profitability efficiency, therefore, hypothesis H2 is accepted.

4.2.3. Default Risk and Marketability Efficiency

A panel VAR model is estimated to analyze the dynamic relationship between default risk and marketability efficiency.

E. Independent Two Stage Model

Results of panel VAR analysis using marketability efficiency scores from independent two stage model are presented below. Lag selection criteria and stability test of panel VAR is stated followed by Granger Causality Wald Tests, VDCs and IRFs. DD is used as a proxy for distance to default and ME is the proxy for marketability efficiency.

E 1. Lag Selection Criteria

The appropriate lag numbers to include in the panel VAR is selected using the model selection criteria of Andrews and Lu (2001) which is based on the GMM estimator. Table 12 a. shows the results of the lag selection criteria. MBIC is minimized and CD is maximized at first lag while j value is also significant at first lag order. Other conditions are relaxed for the sake of parsimony. Therefore, a pVAR of first order is chosen.

Table 12 a. Lag Selection Criteria

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.760345	33.7439	0.00074	-22.9848	9.743899	-3.53705
2	0.627003	18.14182	0.020188	-19.6773	2.141818	-6.71215
3	0.541306	21.85842	0.000214	2.948874	13.85842	9.431443

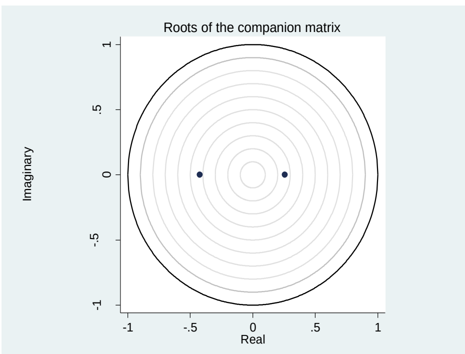
E 2. Stability Testing

Table 11 b. shows that all modulus of each eigenvalue is less than one, hence, stability condition is satisfied.

Table 12 b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.423306	0	0.423306
0.256355	0	0.256355

Figure 10. Eigenvalues of the Companion Matrix



According to Figure 8, all the eigenvalues lie inside the unit circle, therefore, pVAR satisfies stability condition.

E 3. Granger Causality Wald Test

Table 12c shows results of Granger Causality Wald Test. Null hypothesis that marketability efficiency doesn't granger cause distance to default can be rejected at usual confidence interval. However, null hypothesis that distance to default does not granger cause marketability efficiency can be rejected at 95% confidence interval. On the basis of this result, causality is uni-directional i.e. from marketability efficiency to default risk.

Table 12 c. Granger Causality Wald Test

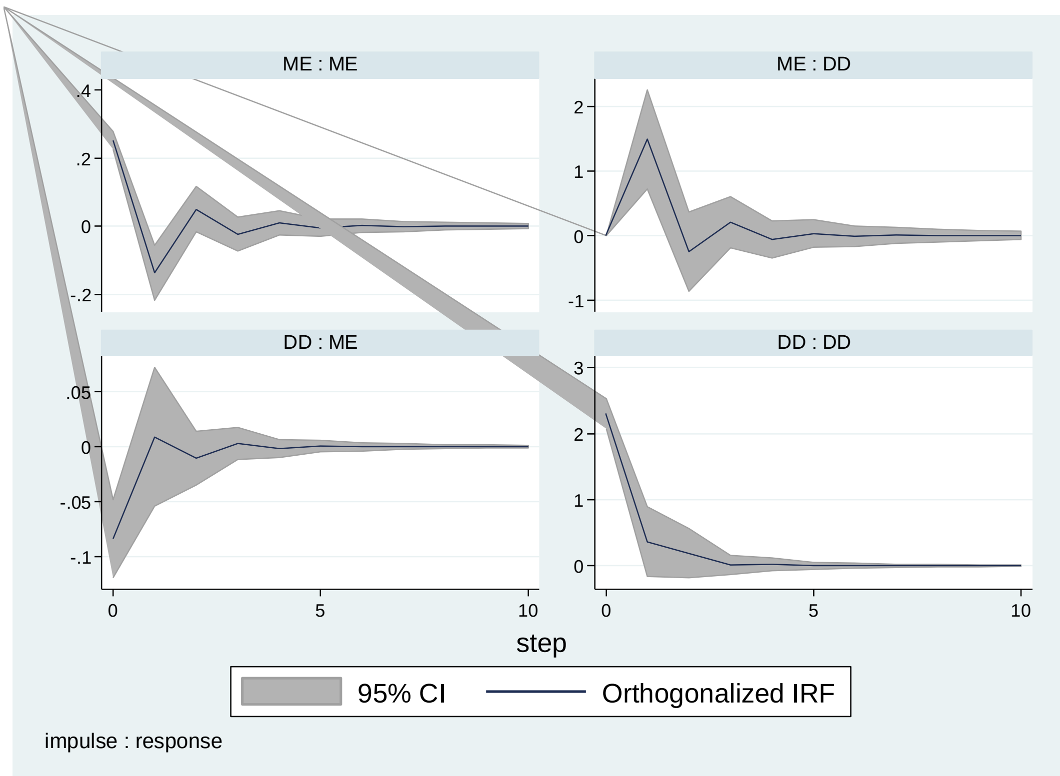
Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	ME	15.789	1	0
	ALL	15.789	1	0
ME				
	DD	0.998	1	0.318
	ALL	0.998	1	0.318

E 4. Impulse Response Functions

Response of distance to default to the shock of marketability efficiency is positive implying a negative relationship between default risk and efficiency with causality going from efficiency to risk. The response is short lived, become insignificant after third year and converges to equilibrium after fifth year.

The response of marketability efficiency towards the shock of DD is temporal and negative which moves towards equilibrium after approximately second period. The result implies that when there is a positive association between marketability efficiency and default risk while causal direction is from risk to efficiency.

Figure 11. Impulse Response Functions



E 5. Forecast Error Variance Decomposition

The results of variance decompositions are presented in Table 12d. The variation caused by marketability efficiency in distance to default are 29.75% after ten years. In contrast, variations in marketability efficiency caused by DD are much smaller (only 7.85%) after a period of ten years. The result also confirms the direction of causality from marketability efficiency to default risk.

Table 12 d. Forecast Error Variance Decomposition

Response Variable and Forecast horizon	Impulse variable	
	DD	ME
DD		
0	0	0
1	1	0
2	0.7109064	0.2890936
3	0.7065834	0.2934166
4	0.7028536	0.2971464
5	0.7025341	0.2974659
6	0.7024411	0.2975589
7	0.7024285	0.2975716
8	0.7024258	0.2975743
9	0.7024253	0.2975747
10	0.7024252	0.2975748
ME		
0	0	0
1	0.1000742	0.8999258
2	0.0800516	0.9199485
3	0.0789915	0.9210085
4	0.0786081	0.921392
5	0.0785603	0.9214396
6	0.0785495	0.9214506
7	0.0785478	0.9214522
8	0.0785474	0.9214525
9	0.0785474	0.9214526
10	0.0785474	0.9214526

F. Relational Two Stage Model

Results of panel VAR analysis using marketability efficiency scores from relational two stage model are presented below. DD is used as a proxy for distance to default and ME is the proxy for marketability efficiency.

F 1. Lag Selection Criteria

The appropriate lag numbers to include in the panel VAR is selected using the model selection criteria of Andrews and Lu (2001) which is based on the GMM estimator. Table 12 a. shows the results of the lag selection criteria. MBIC is minimized and j value is also significant at first lag order. Other conditions are relaxed for the sake of parsimony. Therefore, a pVAR of first order is chosen.

Table 13 a. Lag length criteria

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.526522	36.90546	0.000231	-19.8232	12.90546	-0.37548
2	0.341152	27.04241	0.000695	-10.7767	11.04241	2.188446
3	0.68121	5.857652	0.210034	-13.0519	-2.14235	-6.56933

F 2. Stability Testing

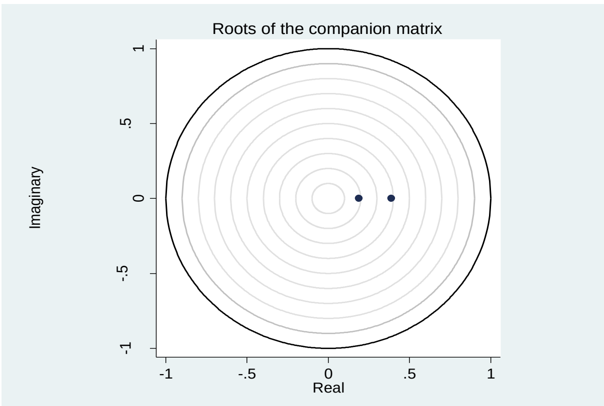
It is evident from the table 13 b. that all egeinvalue modulus are less than unity therefore, panel VAR is stable.

Table 13 b. Moduli of VAR Companion Matrix

Eigenvalue		
Real	Imaginary	Modulus
0.3885591	0	0.3885591
0.1887581	0	0.1887581

Stability of panel VAR is also confirmed by Figure 12 because all the eigenvalues lie inside the unit circle.

Figure 12. Eigenvalues of the Companion Matrix



F3. Granger Causality Wald Test

The results of Granger Causality tests are stated in Table 13 c. According to the results there is no causal relationship between default risk and marketability efficiency and vice versa because in both cases null hypotheses can't be rejected at usual confidence intervals.

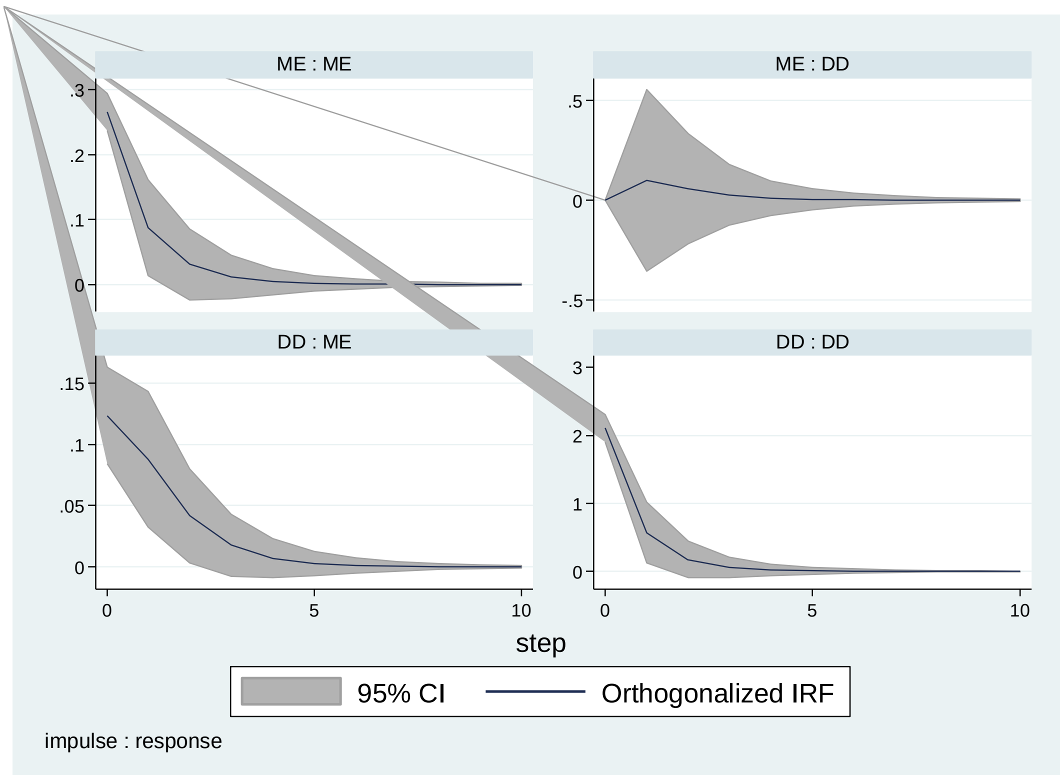
Table 13 c. Granger Causality Test

Equation	Excluded variable	chi2 statistic	chi2	p value
DD				
	ME	0.177	1	0.674
	ALL	0.177	1	0.674
ME				
	DD	2.006	1	0.157
	ALL	2.006	1	0.157

F 4. Impulse Response Function

One standard deviation shock of marketability efficiency create minimal variation in distance to default. However, response of marketability efficiency to distance to default is positive and significant for approximately first four periods. The result implies negative relationship between default risk and efficiency and the direction of relationship is from risk to efficiency.

Figure 13. Impulse Response Functions



F 5. Forecast Error Variance Decomposition

The results of variance decompositions are presented in Table 13d. The variation caused by marketability efficiency in distance to default are negligible and after ten years only 0.29% of DD variations are being caused by marketability efficiency. In contrast, variations in efficiency caused by DD are much larger and after a period of ten years, 23.98% variations of marketability efficiency are being explained by distance to default. This result also implies that causality goes from default risk to efficiency.

Table 13 d. Forecast Error Variance Decomposition

Response Variable and Forecast horizon	Impulse variable	
	DD	ME
DD		
0	0	0
1	1	0
2	0.9979277	0.0020723
3	0.9972564	0.0027436
4	0.9971199	0.0028801
5	0.9970963	0.0029036
6	0.9970926	0.0029074
7	0.997092	0.002908
8	0.9970919	0.0029081
9	0.9970919	0.0029081
10	0.9970919	0.0029081
ME		
0	0	0
1	0.1774045	0.8225955
2	0.2266397	0.7733603
3	0.2374443	0.7625557
4	0.2394069	0.7605931
5	0.2397311	0.7602689
6	0.2397822	0.7602178
7	0.2397901	0.7602099
8	0.2397913	0.7602087
9	0.2397915	0.7602085
10	0.2397915	0.7602085

Results of panel VAR model confirm the existence of relationship between default risk and marketability efficiency, therefore, hypothesis H3 is accepted.

CHAPTER 5

DISCUSSION AND CONCLUSION

A panel-VAR approach is applied to model the dynamic interactions between default risk and efficiency of the banks in Pakistan. The aim of the study was to interpret whether sustained financial stability and the gains in profitability, marketability and overall efficiency of the banks are mutually exclusive objectives or these are interrelated. The results reveal some interesting findings regarding the dynamic interaction between efficiency and risk in the context of a developing country of South Asia. Merton's distance to default model is used to measure distance to default. Distance to default is used as a measure of financial stability. Two stage production process of banks is used to measure efficiency scores by applying two types of models (independent and relational model). The results of panel VAR analysis confirm the existence of relationship between default risk and the three facets of bank efficiency (profitability, marketability and overall efficiency).

In terms of the relationship between default risk and overall efficiency, IRFs and VDCs show that relationship direction goes from default risk to overall efficiency. The relationship is found to be negative. The results support the bad luck hypothesis proposed by Berger and Deyoung (1997). The reverse direction of relationship is not refuted, but evidence is weaker. The direction of relationship is negative which support the bad management hypothesis developed by Berger and DeYoung (1997).

The results of panel VAR analysis between profitability efficiency and default risk show negative relationship between profitability and risk with the direction of the relationship from profitability efficiency to risk. The reverse direction of the relationship is found to be negative and weaker. Thus, the results provide strong support for bad management hypothesis than the bad luck hypothesis.

Results obtained by using the efficiency scores of independent and relational model are similar in the case of panel VAR analysis between overall efficiency and default risk as well as the panel VAR analysis of profitability efficiency and default risk. However, in case of panel VAR analysis between default risk and marketability efficiency, the results differ by using the scores from the relational model and independent model. In the panel VAR analysis, the efficiency scores from independent model provide support for bad management hypothesis because the direction goes from marketability efficiency to risk and both are negatively associated. However, the use of efficiency scores of relational model provides evidence of negative relationship between risk and marketability efficiency. The direction of relationship is from risk to marketability efficiency which is in line with the bad luck hypothesis proposed by Berger and DeYoung (1997).

5.1. Recommendations and Policy Implications

The panel VAR analysis of default risk and efficiency has several policy implications. The results of the study imply complex interdependency between financial stability and the overall, profitability and marketability efficiency level because default risk estimated by distance to default is assumed to be a measure of financial stability. The results reveal that, in case of profitability efficiency, the relationship runs from efficiency to risk. Therefore, efficiency enhancing mechanisms need to be managed in such a way that will help in improving the stability of financial institutions. The results found an absence of tradeoff between the performance of financial institutions in the stock market and the financial stability. Therefore, directing efforts towards improving the performance of financial institutions in the stock markets will result in financial stability improvements. This result also hints the importance of efficient functioning of stock markets in ensuring stability of the financial system at large. The relationship direction from default risk to overall efficiency implies that distance to default can not only work as a signal of financial instability but also it can be an early warning signal of inefficiency of the overall production process of a bank. This highlights the importance of distance to default because controlling the distance to default of financial institutions will helps in improving efficiency level besides preparing them to combat a potential financial crisis.

5.2. Limitations of the Study

The study is limited to the banks of Pakistan due to the issue of data unavailability. The banks which are listed on the Pakistan Stock exchange are considered because the data of share prices and market capitalization was needed for the calculation of distance to default and the data was also required to be used as output for efficiency score calculation.

5.3. Future Research Directions

In the current study, the efficiency is measured by using a non-parametric approach (DEA). However, by employing multiple parametric and non-parametric approaches, it would be interesting to find out that whether the relationship between default risk and efficiency is sensitive to the choice of approach to measure efficiency. The efficiency measurement in two stage model are based upon the assumption of constant returns to scale. In the presence of imperfect competition, the condition of constant returns to scale model that all decision making units are operating at optimal level is often impossible to fulfil. Therefore, in future, a more recent two-stage DEA model under the condition of variable returns to scale can be applied to measure efficiency. For the sake of robustness, multiple techniques can be used to measure the default risk of banks. Further researchers can also perform a regional comparison to find out whether the risk and efficiency nexus of financial institutions differs across regions.

REFERENCES

Abbas, A., Zaidi, S. A. H., Ahmad, W., & Ashraf, R. U. (2014). Credit Risk Exposure and Performance of Banking Sector of Pakistan. *J. Basic. Appl. Sci. Res*, *4*(3), 240–245.

Abbas, M., Azid, T., & Hj Besar, M. H. A. (2016). Efficiency, effectiveness and performance profile of Islamic and conventional banks in Pakistan. *Humanomics*, *32*(1), 2–18. http://doi.org/10.1108/H-09-2015-0058

Abrigo, M. R., & Love, I. (2015). Estimation of panel vector autoregression in Stata: A package of programs. manuscript, Febr 2015 available on http://paneldataconference2015. ceu. hu/Program/Michael-Abrigo. pdf.

Agnello, L., Sousa, R., 2011. How do banking crises impact on income inequality? NIPE Working Papers 30. University of Minho

Aharony, J., & Swary, I. (1996). Additional evidence on the information-based contagion effects of bank failures. *Journal of Banking & Finance*,*20*(1), 57-69.

Ahmad, N. H., & Ariff, M. (2007). Multi-country study of bank credit risk determinants. *International Journal of Banking and Finance*, *5*(1), 6.

Akhtar, M. H. (2002). X-efficiency analysis of commercial banks in Pakistan: A preliminary investigation. *Pakistan Development Review*, *41*(4 PART 2), 567–580.

Allen, D., & Powell, R. (2011). Credit risk measurement methodologies.

Amel, D., C. Barnes, F. Panetta, and C. Salleo (2004). Consolidation and Efficiency in the Financial Sector: A Review of the International Evidence. Journal of Banking & Finance 28(10), 2493-2519.

Andrews, D. W., & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, *101*(1), 123-164.

Ariss, R. T. (2010). On the implications of market power in banking: Evidence from developing countries. Journal of Banking and Finance, 34(4), 765-775.

Ataullah, A., Cockerill, T., & Le, H. (2004). Financial liberalization and bank efficiency: a comparative analysis of India and Pakistan. *Applied Economics*, *36*(17), 1915–1924. https://doi.org/10.1080/000368404200068638

Avkiran, N. K. (2011). Association of DEA super-ef? ciency estimates with ? nancial ratios: Investigating the case for Chinese banks. OMEGA, The International Journal of Management Science, 39(3), 323-334. dx.doi.org/10.1016/j. omega.2010.08.001.

Bank of International Settlements, Basel Committee on Banking Supervision, 2002. Supervisory Guidance on Dealing with Weak Banks.

Barr, R.S., Siems, T.F., 1994. Predicting bank failure prediction using DEA to quantify management quality. Federal Reserve Bank of Dallas, Financial Industry Studies Working Paper N0. 1-94.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870. https://doi.org/10.1016/S0378-4266(97)00003-4.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. The journal of political economy, 637-654

Boyd, J.H, De Nicolo, G. 2005. The Theory of Bank Risk Taking and Competition Revisited. Journal of Finance, LX, 1329 - 1343 .

Castelli, Lorenzo, Raffaele Pesenti, and Walter Ukovich. "A classification of DEA models when the internal structure of the decision making units is considered." *Annals of Operations Research* 173.1 (2010): 207-235.

Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling*, *31*, 672-683.

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in International Business and Finance*, *33*(August 2016), 1–16. https://doi.org/10.1016/j.ribaf.2014.06.001

Chan-Lau, J.A., Jobert, A., Kong, J., 2004. An option-based approach to bank vulnerabilities in emerging markets. International Monetary Fund Working Paper WP/04/33.

Charnes, A., Cooper, W.W., 1984. The non-Archimedean CCR ratio for efficiency analysis: A rejoinder to Boyd and Fa¨re. European Journal of Operational Research 15, 333–334.

Charnes, A., Cooper, W.W., Rhodes, E.L., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–444.

Chen, M.-J., Chiu, Y.-H., Jan, C., Chen, Y.-C., & Liu, H.-H. (2015). Efficiency and Risk in Commercial Banks – Hybrid DEA Estimation. *Global Economic Review*, *44*(3), 335–352. https://doi.org/10.1080/1226508X.2015.1067865.

Chen, X., 2007. Banking deregulation and credit risk: Evidence from the EU. Journal of Financial Stability 2, 356-390.

Cheng, G., Zervopoulos, P., & Qian, Z. (2013). A variant of radial measure capable of dealing with negative inputs and outputs in data envelopment analysis. *European Journal of Operational Research*, *225*(1), 100-105.

Chiu, Y.-H., Chen, Y.-C., & Bai, X.-J. (2011). Efficiency and risk in Taiwan banking: SBM super-DEA estimation. *Applied Economics*, *43*(5), 587–602. https://doi.org/10.1080/00036840802599750

Cleary, S., & Hebb, G. (2016). An efficient and functional model for predicting bank distress: In and out of sample evidence. *Journal of Banking and Finance, 64*, 101–111.

Dima, B., Dincă, M. S., and Spulbăr, C. (2014). Financial nexus: Efficiency and soundness in banking and capital markets. Journal of International Money and Finance, 47, 100- 124.

Drucker P. F. Managing for business effectiveness. Harvard Business Review 1963; Vol. 41: 53-60.

Eken, M. H., & Kale, S. (2013). Evaluating the efficiency of Turkish banks: a risk and profitability approach. *Journal of CENTRUM Cathedra: The Business and Economics Research Journal*, *6*(1), 53-68.

Emrouznejad A., Anouze A.L. and Thanassoulis E. (2010). A semi-oriented radial measure formeasuring the efficiency of decision making units with negative data, using DEA. European Journal of Operational Research. 200: 297-304.

Fama, E., 1965. The behavior of stock market prices. Journal of Business 38, 34–105.

Farrell, M.J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society (A, general), 120: 253–281.

Festić, M., Kavkler, A., & Repina, S. (2011). The macroeconomic sources of systemic risk in the banking sectors of five new EU member states. *Journal of Banking & Finance*, *35*(2), 310-322.

Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research*, *204*(2), 189-198.

Fiordelisi, F., Marques-Ibanez, D., & Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking and Finance*, *35*(5), 1315–1326.

Fiordelisi, F., and Mare, D. S. (2014). Competition and financial stability in European cooperative banks. Journal of International Money and Finance, 45, 1-16.

Funso, K., Kolade, A., & Ojo, O. (2012). Credit risk and commercial banks' performance in Nigeria: A panel model approach. *Australian Journal of Business and Management Research*, *2*(02), 31–38.

Gorton, G., Rosen, R., 1995. Corporate control, portfolio choice and the decline of banking. Journal of Finance 50(5), 1377-1420.

Gropp, R., Vesala, J., Vulpes, G., 2004. Market indicators, bank fragility, and indirect market discipline. Federal Reserve Bank of New York Economic Policy Review 10, 53–62.

Harada, K., Ito, T., and Takahashi, S. (2010). Is the distance to default a good measure in predicting bank failures? Case studies: National Bureau of Economic Research

Heizer, J. and Render, B. (2006), Operations Management, 8th ed., Pearson Education Inc, Upper Saddle River, NJ.

Hensel, N.D. (2003), "Strategic management of efficiencies in networks: cross-country evidence on European branch banking", European Financial Management, Vol. 9 No. 3, pp. 333-360.

Hughes, J.P. (1999). Incorporating risk into the analysis of production. *Atlantic Economic Journal* 27(1),1-23.

Hull, J.C., 1999. Options, futures, and other derivatives. Pearson Education India

Jessen, C., & Lando, D. (2015). Robustness of distance-to-default. *Journal of Banking and Finance*, *50*(May), 493–505. https://doi.org/10.1016/j.jbankfin.2014.05.016

Kabir, M. N., Worthington, A., & Gupta, R. (2015). Comparative credit risk in Islamic and conventional bank. *Pacific Basin Finance Journal*, *34*, 327–353. https://doi.org/10.1016/j.pacfin.2015.06.001

Kao, C., & Hwang, S. N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *European Journal of Operational Research*, *185*(1), 418–429. https://doi.org/10.1016/j.ejor.2006.11.041.

KMV, C., 1993. Credit monitor overview. San Francisco California, 60-66

Koetter, M., & Porath, D. (2007). Efficient, profitable and safe banking: an oxymoron? Evidence from a panel VAR approach. *Discussion Paper Series 2: Banking and Financial Studies*, (2). Retrieved from http://ideas.repec.org/p/zbw/bubdp2/5354.html

Koutsomanoli-Filippaki, A., & Mamatzakis, E. (2009). Performance and Merton-type default risk of listed banks in the EU: A panel VAR approach. *Journal of Banking and Finance*, *33*(11), 2050–2061. https://doi.org/10.1016/j.jbankfin.2009.05.009

Kumar, V. (2016). Evaluating the financial performance and financial stability of national commercial banks in the UAE. *International Journal of Business and Globalisation*, *16*(2), 109-128.

Liu, J. S., Lu, L.Y.Y., Lu, W-M and Lin, B.J.Y. (2013) Data envelopment analysis 1978–2010: A citation-based literature survey Omega 41: 3-15.

Lo, S. F. (2010). Performance evaluation for sustainable business: A profitability and marketability framework. *Corporate Social Responsibility and Environmental Management*, *17*(6), 311–319. https://doi.org/10.1002/csr.214

Lo, S.F., & Lu, W.M. (2006). Does Size Matter? Finding the Profitability and Marketability Benchmark of Financial Holding Companies. *Asia-Pacific Journal of Operational Research*, *23*(2), 229–246. https://doi.org/10.1142/S0217595906000930

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*, *46*(2), 190-210.

Lovell, C.A.K., Pastor, J.T., 1995. Units invariant and translation invariant DEA models. Operations Research Letters 18, 147–151.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012-1027.

Lu, W. M., & Hung, S. W. (2009). Evaluating profitability and marketability of Taiwan's IC fabless firms: An DEA approach. *Journal of Scientific and Industrial Research*, *68*(10), 851–857.

Luo, X. (2003). Evaluating the profitability and marketability efficiency of large banks: An application of data envelopment analysis. *Journal of Business Research*, *56*(8), 627–635. https://doi.org/10.1016/S0148-2963(01)00293-4.

Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.

Minsky, H. P (1992). The Financial Instability Hypothesis, Working Paper No. 74, May, pp. 6-8.

Mohd Tahir, I., Abu Bakar, N. M., & Haron, S. (2009). Evaluating Efficiency of Malaysian Banks Using Data Envelopment Analysis. *International Journal of Business and Management*, *4*(8), 96–106.

Mostafa, M. (2007). Modeling the efficiency of GCC banks: a data envelopment analysis approach. *International Journal of Productivity and Performance Management*, *56*(7), 623–643. https://doi.org/10.1108/17410400710823651.

Nurul, K. M., & Worthington, A. C. (2015). *The 'Competition–Stability Nexus': Is Efficiency an Appropriate Channel?* (No. finance: 201514). Griffith University, Department of Accounting, Finance and Economics.

Olson, D. and Zoubi, T.A. (2011) 'Efficiency and bank profitability in MENA countries', Emerging Markets Review, Vol. 12, pp.94–110.

Ong M.: Internal Credit Risk Models – Capital Allocation and Performance Measure- ment. Risk Books, 2005.

Pasiouras, F. (2008). Estimating the technical and scale efficiency of Greek commercial banks: The impact of credit risk, off-balance sheet activities, and international operations. *Research in International Business and Finance*, *22*(3), 301–318.

Pastor, J.M., Serrano, L. 2005. Efficiency, endogenous and exogenous credit risk in the banking systems of the Euro area. *Applied Financial Economics* 15, 631-649.

Petersen, M. A., and Rajan, R. G. (1995). The effect of credit market competition on lending relationships. The Quarterly Journal of Economics, 407-443.

Podpiera, A., & Podpiera, J. (2005). Deteriorating Cost Efficiency in Commercial Banks Signals an Increasing Risk of Failure. *Economic Change and Restructuring*, *41*(3), 209–219.

Podpiera, J., & Weill, L. (2008). Bad Luck or Bad Management? Emerging Banking Market Experience. *Journal of Financial Stability*, *4*(2), 135–148.

Portela, M.C.A.S., Thanassoulis, E. and Simpson, G. (2004). Negative data in DEA: a directional distance approach applied to bank branches. Journal of the Operational Research Society. 55: 1111-1121.

Reynaud, J. P. M. (2010). Could Efficiency Analysis Help in Predicting Bank Failure? The Case of the 2001 Turkish Crisis. *Review of Middle East Economics and Finance*, *6*(1).

Rossi, S. P., Schwaiger, M., & Winkler, G. (2005). *Managerial behavior and cost/profit efficiency in the banking sectors of Central and Eastern European countries*. Oesterr. Nationalbank.

Ruggiero, J.A. (2007), "A comparison of DEA and the stochastic frontier model using panel data", International Transactions in Operational Research, Vol. 14 No. 3, pp. 259-266.

Saeed, M., & Izzeldin, M. (2014). Examining the relationship between default risk and efficiency in Islamic and conventional banks. *Journal of Economic Behavior and Organization*. https://doi.org/10.1016/j.jebo.2014.02.014.

Schaeck, K., & Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management*, *43*(1), 215-241.

Seiford, L. M., & Zhu, J. (1999). Profitability and Marketability of the Top 55 U.S. Commercial Banks. *Management Science*, *45*(9), 1270–1288.

Sena, V. (2003). The frontier approach to the measurement of productivity and technical efficiency. *Economic Issues-Stoke On Trent*, *8*(2), 71-98.

Shahid, H., Rehman, R. U., Niazi, G. S. K., & Raoof, A. (2010). Efficiencies comparison of Islamic and conventional banks of Pakistan. *International Research Journal of Finance and Economics*, *49*(9), 24–42. https://doi.org/10.5539/ijbm.v5n2p137

Shahwan, T. M., & Hassan, Y. M. (2013). Efficiency analysis of UAE banks using data envelopment analysis. *Journal of Economic and Administrative Sciences*, *29*(1), 4–20. https://doi.org/http://dx.doi.org/10.1108/10264111311319204

Sohail, M. K., & Anjum, M. S. (2016). Efficiency Dynamics of Initial Public Offerings Using Data Envelopment Analysis and Malmquist Productivity Index Approach. *Engineering Economics*, *27*(2), 175–184.

Tabak, B. M., Craveiro, G. L., & Cajueiro, D. O. (2011). *Bank efficiency and default in Brazil: Causality tests* (No. 253).

Wheelock, D., & Wilson, P. (1995). Explaining bank failures: Deposit insurance, regulation, and efficiency. *The Review of Economics and Statistics* 77, 689-700.

Wheelock, D., & Wilson, P. (2000). Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions. *The Review of Economics and Statistics*, *82*(1), 127–138.

Williams, J. (2004). Determining management behaviour in European banking. *Journal of Banking & Finance*, *28*(10), 2427-2460.

Yildirim, H.S., and G.C. Philipatos. 2007. Bank efficiency: Evidence from the transition economies of Europe. European Journal of Finance 13, no. 2: 123–43.

Yue, P. (1992) Date envelopment analysis and commercial bank performance:Aprimer with applications to Missouri banks, Federal Reserve Bank of St. Louis Review, 74(1), pp. 31–45.

APPENDIX

Panel VAR Estimates:

1. **Overall Efficiency and Default Risk**

Table A. Panel VAR Estimates (Efficiency scores derived from Independent Two Stage Model):

	Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t						
DD_{t-1}	0.1853708	0.092218	2.01	0.044	0.004627	0.366115
E_{t-1}	1.699986	1.121564	1.52	0.13	-0.49824	3.898211
E_t						
DD_{t-1}	0.022795	0.010622	2.15	0.032	0.001977	0.043613
E_{t-1}	0.5650354	0.110126	5.13	0	0.349193	0.780878
No. of obs = 179						
No. of panels = 22						
Ave. no. of T = 8.136						
Final GMM Criterion Q(b) = .25						

Table B. Panel VAR Estimates (Efficiency scores derived from Relational Two Stage Model):

	Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t						
DD_{t-1}	0.375393	0.124778	3.01	0.003	0.130833	0.619954
E_{t-1}	-1.57662	1.411981	-1.12	0.264	-4.34405	1.190814
E_t						
DD_{t-1}	0.020754	0.010472	1.98	0.047	0.00023	0.041279
E_{t-1}	0.214511	0.1524423	1.41	0.159	-0.0842704	0.5132924

No. of obs = 179
No. of panels = 22
Ave. no. of T = 8.136
Final GMM Criterion Q(b) = .25
Instruments lags (1/4) of (DD E)

2. Profitability Efficiency and Default Risk

Table C. Panel VAR Estimates (Efficiency scores derived from Independent Two Stage Model)

		Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t							
	DD_{t-1}	0.123268	0.120689	1.02	0.307	-0.11328	0.359814
	PE_{t-1}	14.31654	3.999264	3.58	0	6.478124	22.15495
PE_t							
	DD_{t-1}	0.014858	0.006202	2.4	0.017	0.002703	0.027013
	PE_{t-1}	0.458747	0.234481	1.96	0.05	-0.00083	0.918321

No. of obs = 179
No. of panels = 22
Ave. no. of T = 8.136
Final GMM Criterion Q(b) = .127
Instruments: lags (1/4) of (DD PE)

Table D. Panel VAR Estimates (Efficiency scores derived from Relational Two Stage Model)

	Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t						
DD_{t-1}	0.375393	0.124778	3.01	0.003	0.130833	0.619954
E_{t-1}	-1.57662	1.411981	-1.12	0.264	-4.34405	1.190814
E_t						
DD_{t-1}	0.020754	0.010472	1.98	0.047	0.00023	0.041279
E_{t-1}	0.214511	0.1524423	1.41	0.159	-0.0842704	0.5132924

No. of obs = 157
No. of panels = 22
Ave. no. of T = 7.136

Final GMM Criterion Q(b) = .109
Instruments lags (2/5) of (DD PE)

3. Marketability Efficiency and Default Risk

Table E. Panel VAR Estimates (Efficiency scores derived from Independent Two Stage Model)

		Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t							
	DD_{t-1}	0.373732	0.11272	3.32	0.001	0.152805	0.59466
	ME_{t-1}	5.915829	1.488789	3.97	0	2.997856	8.833802
ME_t							
	DD_{t-1}	-0.01581	0.015834	-1	0.318	-0.04685	0.015219
	ME_{t-1}	-0.54068	0.160965	-3.36	0.001	-0.85617	-0.2252

No. of obs = 179
No. of panels = 22
Ave. no. of T = 8.136
Final GMM Criterion Q(b) = .174
Instruments: lags (1/4) of (DD ME)

Table F. Panel VAR Estimates (Efficiency scores derived from Relational Two Stage Model)

		Coefficient	Standard Error	z value	p value	95% Confidence Interval	
DD_t							
	DD_{t-1}	0.248717	0.123507	2.01	0.044	0.006647	0.490786
	ME_{t-1}	0.373847	0.888461	0.42	0.674	-1.36751	2.115199
ME_t							
	DD_{t-1}	0.022428	0.015835	1.42	0.157	-0.00861	0.053465
	ME_{t-1}	0.328601	0.125853	2.61	0.009	0.081933	0.575268

No. of obs = 179
No. of panels = 22
Ave. no. of T = 8.136

Final GMM Criterion Q(b) = .229
Instruments: lags (1/4) of (DD ME)